Discussion Paper No. 1169

INFORMATION AND ORGANIZATION FOR HORIZONTAL MULTIMARKET COORDINATION*

by

Krishnan S. Anand
Northwestern University

and

Haim Mendelson
Stanford University

* This paper has greatly benefitted from the comments and suggestions of the Associate Editor and the anonymous referees. Partial financial support by the Stanford Computer Industry Project is gratefully acknowledged.

Information and Organization for Horizontal Multimarket Coordination *

Krishnan S. Anand
J.L.Kellogg Graduate School of Management
Northwestern University
Evanston, IL 60208-2001

Haim Mendelson
Graduate School of Business
Stanford University
Stanford, CA 94305-5015

Management Science, *forthcoming*

*This paper has greatly benefitted from the comments and suggestions of the Associate Editor and the anonymous referees. Partial financial support by the Stanford Computer Industry Project is gratefully acknowledged.

Abstract

We model the effects of alternative coordination structures on the performance of a firm that faces uncertain demand in multiple horizontal markets. The firm's coordination structure is jointly determined by its decision-rights structure and by its information structure. We compare the performance of decentralized, centralized and distributed structures and study factors that affect the value of coordination. The results quantify and illustrate the value of co-locating decision rights with specific knowledge.

1 Introduction

Information Technology (IT) has a profound impact on the coordination structure of organizations [27, 28]. In this paper, we propose a theoretical framework for studying the impact of alternative coordination structures, modeling a firm that faces uncertain demand in multiple horizontal markets (e.g., geographical regions or countries). The firm selects a coordination structure by jointly determining its decision authority structure ("who decides what") and its information structure ("who knows what"). This analysis extends and operationalizes key aspects of the Jensen-Meckling [26] (JM) approach to the design of organizations.

Demand uncertainty has always been an important feature of business environments. Proliferation in product varieties, shorter product cycles and the volatility of the global marketplace increase demand uncertainty for any given product, resulting in unmet demand or price markdowns [15]. General Motors, for example, loses upwards of 20% of potential sales because the desired vehicle is not available within its customers' wait tolerance, and over 40% of its customers buy a "compromise" vehicle [19]. In the apparel industry, the cost of demand uncertainty was estimated at $25 billion per year [16], and department store markdowns have doubled in about ten years [15]. These effects were important in the business failures of ill-prepared retailers such as Best Products, Carter Hawley Hale, Hills, Paul Harris and Gantos.

In contrast, the superior performance of firms like Wal-Mart, The Gap, The Limited and Benetton is due in large measure to their ability to manage demand uncertainty using "accurate response" [15] strategies. To quote a senior executive at the retail chain Mervyn's, "to compete effectively, we must be able to identify trends in the stores immediately and react swiftly to different sales patterns" [11]. Wal-Mart and The Limited use electronic links with suppliers to reduce order cycle time and base stocking decisions on observed early sales rather than pure hunches [14].

IT enables firms to effectively cope with demand uncertainty. Specialty retailers such as The Gap, The Limited and Toys "R" Us were among the first to invest in systems to automatically reorder popular items and mark down slow sellers on a weekly or even daily basis. For example, Toys "R" Us has its Point of Sales (POS) data relayed instantly to headquarters, where it is used to pinpoint the hot sellers and the duds for the all-important Christmas Season [13]. KMart invested $1 billion in a nationwide POS system linking 2,250 branches to corporate headquarters by satellite to track daily sales and respond to market shifts. This resulted in reported savings of $87 million for the 1990 Christmas Season [29]. J.C. Penney [32] installed computerized inventory systems that use POS scanner data to automatically reorder products from 281 suppliers, or roughly half of their $12 billion annual sales. Service Merchandise has a system that suggests stock orders and even stock transfers [32]. Wal-Mart uses checkout scanners to transmit POS data via satellite to its suppliers' systems, to speed up inventory replenishments and minimize stockouts [39]. Other examples include apparel manufacturers such as Levi Strauss, Haggar, Arrow, The Gap and Sport Obermeyer, who use information systems (IS) to monitor market trends in styles, sizes and colors. To be effective, however, these IS must be harmonized with the structure of the organizations they support. We argue that both the firm's organizational structure and its IS should be viewed as part of an integrated architecture – the *coordination structure* of the firm.

The economics of organizational design is an active area of research. Radner [37, 38] motivates the economic analysis of "managing" and studies efficient information processing networks in terms of the tradeoff between delay and number of processors. Other recent research addresses the efficient allocation of tasks within a firm when information processing is costly [1, 10, 17], tradeoffs between coordination and delay costs in hierarchical information structures [1], hierarchies arising from bounded rationality [17], organizational returns to scale [40], tradeoffs between specialization and coordination under information processing and communications costs [5] and centralization vs. decentralization in the context of delay costs [6]. "Coordination Science" is fast developing as an area of research in its own right [27, 28].

Three key determinants of a firm's structure are the power to make decisions ('decision rights'), decision-makers' incentives and the firm's information structure (IS).[1] While JM [25, 26] focus on

[1]The firm's information systems implement its information structure. We use the acronym IS for both.

the role of incentives and the allocation of decision rights, our emphasis is on the joint determination of decision rights and the firm's information structure, and the associated value of alternative IS. We model a profit-maximizing manufacturing firm that sells its product in several horizontal markets that are subject to demand uncertainty. The firm's marginal cost function is increasing, giving rise to potential coordination problems: when the decisions on how much to sell in each market are made without knowing total production, decision makers do not know the effective marginal cost they face. These coordination problems are confounded by the fact that different decision-makers have different information sets available and hence differ in their market assessments. The firm has to design its coordination structure, which determines (*i*) who makes the quantity decisions for each market, and (*ii*) what information is available to each decision maker. Our main model differentiates demand information into *local knowledge* that cannot be communicated (such as a 'feel' for local market conditions) and *data* that can be (e.g., past sales). We focus on the case where the firm's decision makers operate as a team, but we also consider the use of transfer pricing to resolve or mitigate incentive problems.

We model three coordination structures (CS): (*i*) the centralized CS, where the center makes all the decisions using all the data but none of the local knowledge, (*ii*) decentralized CS, where each branch makes its own sales decision based on its own local knowledge and data, and (*iii*) fully distributed CS, where all data are shared and hence each branch makes its decisions based on both its own local knowledge and all the data. The fully-distributed CS does better than both the decentralized CS, where branches cannot share their data, and the centralized CS, which fails to exploit local knowledge. The relative performance of the centralized and decentralized CS depends on additional model parameters.

We define the value of coordination (VOC) as the profit difference between the distributed and decentralized CS. VOC is at first increasing in the number of branches and then – strictly decreasing. For a large number of markets, the decentralized CS does almost as well as the fully distributed CS. This suggests that distributed systems would add more value to firms operating in a small to medium number of markets than to those operating in many independent markets.

Our primary model assumes that decision makers behave as a team and that demand curves are statistically independent across markets. The results underscore the importance of local knowledge, which is not amenable to statistical aggregation, for effective decision making, and link the location of specific knowledge to organizational and IS design. We find that in a variety of cases, the performance of decentralized CS dominates that of centralized CS in spite of the latter's superior coordination. In the special case where local knowledge is of little value, the centralized CS does better for a small number of markets. However, as the number of markets increases, this performance gap decreases, and eventually, the decentralized regime does as well or better. Further, the profits of CS that tap into local knowledge are convex functions of its precision, i.e., there are increasing returns to local knowledge. Our results also demonstrate that knowledge and data are complements (however, they may be substitutes under alternative model specifications). Thus, the availability of specific market knowledge need not diminish the value of IS, which may provide useful complementary information, depending on the structure of the demand shocks.

We study an alternative model where the demand states are linked by an aggregate shock. For a large number of branches, the VOC tends to zero in spite of the dependence across markets, and data and local knowledge remain complements. We further introduce specific knowledge of overall market factors that resides with the center. As a result, the Centralized CS becomes more attractive, since the allocation of decision rights has to trade off the loss of local specific knowledge against the loss of central specific knowledge. We illustrate how the relation between the precisions of the two types of specific knowledge affect the choice of CS.

We also relax the team assumption and allow for self-maximizing decision makers. We show how transfer pricing can resolve incentive problems. We then consider *determinate* transfer pricing schemes where each branch faces a fixed price-quantity schedule, and derive the optimal scheme and the associated agency costs. We find that agency costs sometimes undermine the advantages of distributed systems, a result that links their use to the firm's incentive structure.

The rest of the paper is organized as follows. The next Section develops our modeling framework. Section 3 provides the optimal team solutions and their implications. Section 4 examines the effect of agency problems. Section 5 studies the effects of demand correlations in a model with aggregate shocks. Our concluding remarks are in Section 6.

2 The Model

2.1 Background and General Framework

Hayek articulated the role of markets as aggregators of idiosyncratic pieces of knowledge that are specific in time, place or circumstance: "It is with respect to this that practically every individual has some advantage over all others in that he possesses unique information of which beneficial use might be made, but of which use can be made only if the decisions depending on it are made with his active cooperation" ([24], pp. 521-522). He pointed out that centrally-planned economies are destined to fail because no central planner(s) could ever assimilate the diverse bits and pieces of information that are necessary for optimizing the economy even if they had the incentive to do so. In contrast, the market system lets individual decision makers act in the light of their own (limited) knowledge; market prices serve as efficient aggregators of information, allow individual agents to maximize their own welfare, and in the process – lead the economy to an efficient equilibrium.

Jensen and Meckling [25, 26] apply similar ideas to the design of organizations. JM [26] argue that whereas in a market system, ownership rights largely solve the twin problems of rights assignment and control, their unavailability within the firm requires alternative solutions. In the JM view, the design of an organization requires the specification of *(i)* decision rights that assign responsibility for decisions to individuals or groups; *(ii)* reward and punishment rules based on decision makers' performance; and *(iii)* monitoring mechanisms to evaluate performance.

JM [26] recognize that organizations must cope with limited information processing capabilities. They distinguish between "specific" knowledge, which is costly to transfer among agents, and "general" knowledge which is inexpensive to transmit. If the center retains all decision-rights, it incurs costs to obtain information available only to individual agents. On the other hand, decentralization of decision-rights leads to agency problems: an agent's objectives differ from the firm's, and inducing her to act in tune with organizational goals is costly. Thus, a centralized system of control leads to high information costs and low agency costs, whereas a decentralized system leads to the reverse, with the optimum degree of decentralization being determined by balancing these costs (Gurbaxani and Whang [22] provide an excellent overview of these issues).

JM's analysis shows how the location of different types of knowledge drives organizational design. IT, however, reallocates information among decision makers, and hence the IS design problem is necessarily intertwined with that of organizational design [33, 34, 7].

We define a *decision point* as an individual or group responsible for a decision. We call the (initial) allocation of potentially useful information among decision points the *informational endowment* of the firm. We classify decision points' informational endowments into two categories: untransferable *Knowledge* and transferable *Data*. For example, unlike POS data or historical price and quantity summaries that are easily communicated, "intuitions" and expertise regarding market factors that are honed over time by the local sales-force at a particular branch or by a central buyer are not. In our context, the "knowledge" possessed by a decision point cannot be communicated to other decision points, whereas "data" can be. For example, the reaction of store workers at a J.C. Penney store in San Antonio, Texas, to a certain "flashy turtleneck body suit" – that the trendy outfit is attractive but they don't plan to stock it because they "kind of tone things down in south Texas" – is *local knowledge* that is hard to communicate to buyers in New York [18]. J.C. Penney's local knowledge also suggests that some local customers prefer certain color combinations and that others "won't spend more than $18 for a child between the ages of 7 and 14, and $18 is tops and it better be the best" [18]. This contrasts with the transactional *data* in J.C. Penney's systems that is highly communicable.

The firm's IS determines what information will be available to each decision point. Its decision-rights (DR) structure determines what decisions will be made by each decision point. For a given IS, the DR structure thus determines how each decision point will map its information into action. In this paper, we make the IS, determined by the firm's IT choices, a design variable. The firm's problem is then to decide on its *coordination structure* – the combination of IS and DR structures – that will maximize its profits.

2.2 The Model

We consider a firm that produces and sells a homogeneous product in n markets labelled $1, 2, \ldots, n$. The firm consists of a "center" that controls production, and n "branches" (one in each market) that are responsible for sales. The firm's objective is to maximize its overall expected profits. The total cost of quantity Q, $TC(Q)$, is an increasing and quadratic (hence convex) function,

$$TC(Q) = c \cdot Q + \frac{1}{2} \cdot \gamma Q^2. \tag{1}$$

Equivalently, the marginal production cost function is linear and increasing in Q: $MC(Q) = c + \gamma Q$, where $\gamma > 0$. The assumption of increasing marginal costs for a fixed plant capacity is common in the literature (cf. Varian [41, pp. 68-69]) and implies that the production technology is not scalable. Thus, the firm has an incentive to restrict output so as to avoid higher marginal costs.

On the demand side, we assume that the n markets have independent, linear demand curves. A market may be in a 'high-demand' or a 'low-demand' state. The demand curve in each market has a known slope $-b$ ($b \geq 0$) (with $b = 0$ for perfectly competitive markets), but in each market i, the intercept is a random variable that depends on its *state* s_i. In the "high" demand state ($s_i = 1$), the demand in market i is given by $P(q_i) = a_H - b \cdot q_i$, and in the "low" demand state ($s_i = 0$), it is $P(q_i) = a_L - b \cdot q_i$ where $0 < a_L < a_H$. Thus, for shipment quantity q_i to market i, the (random) price is $P_i = a_i - bq_i$, where a_i is a_H if $s_i = 1$ and a_L if $s_i = 0$. We assume that a firm operating in a single market would want to sell positive quantities in either state, and that the branches always operate in the increasing part of their revenue curves, i.e., $a_H > a_L > c$ and $a_L > \frac{2b}{2b+\gamma}(a_H - c)$. The latter assumption is made to ensure that no branch operates in a range where selling more quantities decreases its revenues.

We assume that each branch is a decision point i possessing information Ψ_i consisting of *(i)* knowledge or data that were part of i's initial endowment, and *(ii)* data that were communicated to i. Similarly, the center, denoted by $i = 0$, is an additional decision point possessing information Ψ_0. The firm's DR structure determines which decision points will decide on the quantity q_i shipped to each branch i. These decisions are made *before* the actual state of demand is known. The firm then produces total quantity $Q = \sum_{i=1}^{n} q_i$ at a cost $TC(Q)$ given by (1), and ships q_i to branch i. Finally, the true state of demand in each market i, and the corresponding sales and profits, are realized.

Our analysis assumes for the most part that decision points act as a *team* [30, 31], i.e., they have the same objective: maximizing the expected overall profits of the firm. This assumes that all incentive problems have been solved, and the focus is on communication and the effective use of information. This approach to the theory of the firm was proposed in the seminal work of Marschak [30] and Marschak and Radner (MR) [31], and our specific setting follows their general formulation. In particular, MR [31, Ch.6] analyze the team decision problem for a quadratic payoff function and derive the corresponding optimality conditions and the system's asymptotic behavior.

Unfortunately, their results are inapplicable to our setting because their decision variables are unconstrained. As a result, applying their generic solution to our problem would require the firm to "buy" the product in the low-demand markets for resale (at a profit) in the high-demand markets. While this type of arbitrage makes sense in other contexts, it does not in ours. Consequently, our qualitative results (Section 3) are sharply different from those obtained under MR's quadratic model. Nevertheless, MR's analysis serves both as a helpful starting point and as an interesting benchmark.

We assume that for all $i = 1, \ldots, n$, the state of demand is given by $s_i = x_i \cdot y_i$, where x_i represents recorded market-i *data* (e.g., POS data) that may be communicated elsewhere, and y_i reflects unobservable local conditions. Local branches can only make an imperfect inference on y_i through a noisy binary signal L_i (discussed below) that represents the local *specific knowledge* of branch i. L_i cannot be communicated to the center, nor to the other branches. We assume that all of $\{x_i, y_i, i = 1, \ldots, n\}$ are independent binary random variables. Let $x_i = 1$ with probability t and 0 with probability $1 - t$ where t is common knowledge (to avoid trivialities, $0 < t < 1$), and let y_i take on the values 0 or 1 with probability $\frac{1}{2}$ each. Thus, $\{s_i\}_{i=1}^{n}$ are independent random variables with $s_i = x_i \cdot y_i$ taking on the value 1 with probability $\frac{t}{2}$ or 0 with probability $(1 - \frac{t}{2})$. The observed local signal L_i captures the value of y_i with imprecision α, i.e., $L_i = y_i$ with probability $(1 - \alpha)$ and $(1 - y_i)$ with probability α; we call $(1 - \alpha)$ the *precision* of the local signal. Without loss of generality, we assume $\alpha \leq \frac{1}{2}$; $\alpha = \frac{1}{2}$ means that L_i gives no information, and $\alpha = 0$ means that L_i fully reveals y_i.

Let $Q^*(s_i)$ denote the quantity sold if there is only a *single* market with *known* demand state s_i, and define $Q_H^* = \frac{a_H - c}{2b+\gamma}$ and $Q_L^* = \frac{a_L - c}{2b+\gamma}$. If $s_i = 1$, $Q^*(s_i)$ is the solution of $\max_q \left\{(a_H - bq)q - (cq + \frac{1}{2}\gamma q^2)\right\}$, which is Q_H^*. Similarly, for $s_i = 0$, $Q^*(s_i) = Q_L^*$. We denote by Q_{-i} the total quantity shipped to all markets *other* than i.

The following Theorem provides the optimality conditions for the team solution. It may be proved by adapting [31, Ch.5, Theorem 4] to the case of non-negative quantities.[2]

Theorem 1 *The optimal quantities must satisfy the equations* $q_i = \max\{E[Q^*(s_i)|\Psi_i] - (\frac{\gamma}{2b+\gamma})E[Q_{-i}|\Psi_i], 0\}$, *where* Ψ_i *is the information available to decision point* i.

[2] We thank an anonymous referee for this suggestion.

Intuitively, each decision point i tries to equate its expected marginal revenue, $E[a_i - 2bq_i|\Psi_i]$, to its expected marginal cost, $c + \gamma E[q_i + Q_{-i}|\Psi_i]$. If $E[Q_{-i}|\Psi_i]$ is too high to have the first order condition satisfied, the optimal order quantity is $q_i = 0$.

2.3 Coordination Structures (CS)

The coordination structures we analyze have a centralized or decentralized DR. When DR are centralized, the center (indexed by 0) is the sole decision point. If DR are decentralized, the branches (indexed by $i = 1, \ldots, n$) make the quantity decisions.

We first anayze the *centralized* (C) CS, where both the DR and the data are centralized. The center knows the values $\{x_i\}_{i=1}^{n}$ of all data items, but not the specific knowledge L_i available locally at the branches. Using the data, the center decides on the order quantity q_i for each branch i. Thus, the knowledge of local market conditions is traded for superior coordination across the branches and the possibility of a more cohesive strategy. Formally, the IS is $\Psi_0 = \{x_1, \ldots, x_n\}$.

The centralized IS can be implemented using a central database into which POS data from the branches are fed via communications lines. Examples of companies that employ such systems abound. The Canadian tire company Kal Tire makes its reordering decisions based on sales data automatically downloaded from 80 tire outlets each night. In Mervyn's, the retail chain, POS data on 300,000 Stock Keeping Units from 286 stores are transmitted via satellite to a central mainframe and are subsequently used for centralized demand trend analysis and purchasing decisions. Another case in point is Mrs. Fields' Cookies, which has a highly centralized system to assist and control most aspects of store operations [36].

Under the *decentralized* (D) CS, each branch i orders quantity q_i based on its own data x_i and specific knowledge L_i, exploiting its superior knowledge of local market conditions. Here, $\Psi_i = \{x_i, L_i\}$ for each i.

Successful companies judiciously exploit both specific and general knowledge by an appropriate combination of decentralization and information-sharing. Thus, DR may be decentralized, but pertinent data are shared by decision points. This is modeled by our *fully distributed* (FD) CS, where each branch i decides on q_i based on *all* the data $x_j, j = 1, \ldots, n$ and its own specific knowledge L_i. Recognizing the need to get more information at the store level, Toys "R" Us installed a system to "gather and disseminate data to its stores nationwide" [8]. Liquor distribution in Saskatchewan, Manitoba and Ontario is done through a distributed system that uses recorded sales data from each store to analyze sales performance and suggest reordering requests, which the store manager can override, alter or approve [42]. Formally, for the FD coordination structure, $\Psi_i = \{x_1, \ldots, x_n; L_i\}$, for each i.

In implementations of the D coordination structure, each branch has its local processing capability with no real-time linkage. The FD coordination structure is typically implemented using networked minicomputers, workstations or PC's, each having real time access to the data throughout the network. Retail operations often combine aspects of both the D and FD CS's. Wal-Mart and J.C. Penney both give store managers considerable autonomy in allocating space and ordering stock, exploiting their knowledge of neighborhood tastes and trends. Yet, their POS data are sent to the firm's computers and information is reported back to the stores. Wal-Mart centralizes most of its pricing, but it identifies 500-600 price-sensitive items on which store managers are required to beat the local competition. Since local competitors' prices are *specific* knowledge, store managers make the pricing decisions on these items. A number of retailers having similar policies go through competitors' racks in the local area daily and record their prices to support pricing decisions.

Finally, we consider the *no information system* (NI) CS, where branches do not have an IS in place to record data. They decide on their order quantities based on just their specific knowledge L_i. Thus, $\Psi_i = \{L_i\}$ for each i.

Figure 1 summarizes the DR and IS structure for the alternative CS that we study and compare. In particular, we study the *value of coordination (VOC)*, defined as the difference in profits between the FD and D coordination structures,[3] and the *value of Information Systems (VOIS)*, which is the profit differential between the D and NI CS's. Since the DR structure is held constant, these are measures of the value of alternative IT implementations.

2.4 Alternative Model Specifications

Clearly, our model is highly stylized, making it important to identify which results are sensitive to model specification. Two key assumptions that require such sensitivity analysis are (*i*) the assumption that the state variable is given by the product (or the minimum) of its components

[3] In our model, coordination manifests primarily as information sharing. More generally, coordination could include additional aspects that are not modelled here.

(viz. $s_i = x_i \cdot y_i = \min\{x_i, y_i\}$) and (*ii*) the independence assumption across markets.

With respect to (*i*), note that if x, y and s are binary and the state s is a non-decresing function $s = f(x, y)$ of both arguments, then the only non-trivial choices for f are $s = \min\{x, y\} = x \cdot y$ (the form assumed by our model) and the alternative form $s = \max\{x, y\}$. We analyzed the model using this alternative specification, confirming that the structure of the solutions and all the qualitative results remain the same with one exception: data and local knowledge become substitutes rather than complements (see Section 3).

With respect to (*ii*), Section 5 studies an alternative model spcification where a common aggregate shock, reflecting macroeconomic events or changes in common tastes, gives rise to correlated demands across markets. Beyond the analysis of sensitivity to the independence assumption, Section 5 also introduces a role for *central* specific knowledge and examines its implications.

3 Analysis of Alternative Coordination Structures (CS)

In this Section, we derive the optimal strategies for each CS, which will enable us to analyze and compare their performance. We first identify common structural characteristics of the solutions that help solve for and interpret the equilibria.

Note that in our model, branches are *ex ante* symmetric. The *ex post* symmetry of the branches depends on the actual information received by them. We call a solution to Theorem 1 *symmetric* if *ex post*, symmetric branches get identical quantities.

Lemma 1 *Under the C,D,FD and NI coordination structures,*

(i) When $b > 0$, there is a unique optimal solution; that solution is symmetric.

(ii) When $b = 0$, there may be multiple optima, but there is a unique symmetric solution.

We thus focus on the symmetric solution for all the CS. The optimal solution can fall into three possible regions. In the *full participation* region, all branches get positive quantities of the good, with the actual quantities depending on market information. At the other extreme is the *exclusive* region, where quantities are shipped only to the branches with the most favorable market information, and all other branches get zero quantities. In the *intermediate* region, some markets get positive quantities and others get zero, depending on market information. When the number of markets is sufficiently large, the solutions for all CS will be *exclusive* with probability 1. The intuitive reason is that with a sufficient number of markets with the most favorable information, there is no need to ship to the less favorable markets.[4]

3.1 The Centralized (C) Coordination Structure

Under the Centralized CS, the center decides on the vector $\underline{q}(\underline{x}) = \{q_i(\underline{x})\}_{i=1}^{n}$ of quantities shipped to each branch i using the *data* $\underline{x} = (x_1, x_2, \ldots, x_n)$. The specific knowledge $L_i, i = 1, \ldots, n$ available to the branches is lost. However, this disadvantage (compared to D) may be offset by the ability to make decisions based on *all* the data $x_i, i = 1, \ldots, n$.

Let $q_x(k)$ denote the center's quantity decision for a branch having $x_i = x$ when $K_n = k$, where K_n is the number of branches having $x_i = 1$. Define $k_C^* = \left\lceil \frac{4b}{\gamma}\left(\frac{Q_L^*}{Q_H^* - Q_L^*}\right)\right\rceil$, where $\lceil\xi\rceil$ denotes the smallest integer $\geq \xi$. For $b > 0$, k_C^* is the critical value separating the fully participating and exclusive regions. For $b = 0$, the solution is fully participating when $k = 0$ and exclusive otherwise. The following Theorem provides the optimal quantities conditional on K_n.

Theorem 2 *: The optimal quantities under the C regime when $K_n = k$ are given by:*

Case 1 $(k = 0)$*:* $q_0(0) = \left(\frac{2b+\gamma}{2b+n\gamma}\right) Q_L^*$.

Case 2 $(k \geq 1)$*:*

$$q_1(k) = \begin{cases} \left(\frac{2b+\gamma}{4b(2b+n\gamma)}\right)[2b \cdot (Q_H^* + Q_L^*) + \gamma(n-k)\cdot(Q_H^* - Q_L^*)], & \text{if } k < k_C^*, \\ \left(\frac{2b+\gamma}{2b+k\gamma}\right)\left(\frac{Q_L^* + Q_H^*}{2}\right), & \text{otherwise.} \end{cases}$$

$$q_0(k) = \begin{cases} \left(\frac{2b+\gamma}{4b(2b+n\gamma)}\right)[4b \cdot Q_L^* - \gamma k \cdot (Q_H^* - Q_L^*)], & \text{if } k < k_C^* \\ 0, & \text{otherwise.} \end{cases}$$

3.2 The Decentralized (D) Coordination Structure

Here, each branch i observes both its own recorded data x_i and its local knowledge L_i and decides on its own quantity q_i. The center then produces $Q = \sum_{i=1}^{n} q_i$.

Let $q_{x\ell}$ be the quantity ordered by a branch i upon observing $(x_i = x, L_i = \ell)$. Note that $q_{00} = q_{01}$, since when $x_i = 0$, $s_i = 0$ irrespective of the value of L_i. Define $T(n) = t(n-1)(\frac{\gamma}{2b+\gamma})$ and $R(\alpha; n) = 1 - \frac{2}{1+(1+T(n))(1-2\alpha)}$, a decreasing function of α in the relevant range. The structure of the optimal solution depends on the values of Q_H^* and Q_L^* and on their relationship to $R(\alpha; n)$.

[4]This result reflects our specific context. In contrast, the solution to the MR [31, Ch.6] model is almost always "fully participating". For large n, markets with unfavorable information receive *negative* quantities, and favorable markets receive positive quantities (larger than in our solution), which is clearly infeasible in our problem.

When $\frac{Q_L^*}{Q_H^*} \leq R(\alpha; n)$, i.e., the relative spread of prices is sufficiently high, the solution falls in the exclusive region: only the branches with the most promising local information ($x = \ell = 1$) order positive quantities, and all others order zero. When $\frac{Q_L^*}{Q_H^*} > R(0; n)$, the optimal solution is fully participating. The intermediate region, in which q_{11} and q_{10} are positive but $q_{00} = 0$, corresponds to $R(\alpha; n) < \frac{Q_L^*}{Q_H^*} \leq R(0; n)$. For this case to apply, there must be some imprecision in the local signal; i.e., $\alpha > 0$. Let

$$\bar{q} = \begin{cases} \frac{t[\alpha Q_L^* + (1-\alpha)Q_H^*]}{2+T(n)}, & \text{in the exclusive region,} \\ \frac{t(Q_L^* + Q_H^*)}{2(1+T(n))}, & \text{in the intermediate region,} \\ \frac{(2-t)Q_L^* + tQ_H^*}{2(1+\frac{(n-1)\gamma}{2b+\gamma})}, & \text{in the full participation region,} \end{cases}$$

where $\bar{q} = (1-t)q_{00} + \frac{t}{2}q_{10} + \frac{t}{2}q_{11}$ is the expected quantity ordered by a branch prior to receiving any information. Thus, $\bar{q}$ is also the quantity that any branch expects any other branch to order in the decentralized regime. The equilibrium quantities $q_{x\ell}$ are given by the following Theorem.

Theorem 3 : *The quantities ordered under the D regime are as follows:*

$$q_{11} = \alpha Q_L^* + (1-\alpha)Q_H^* - (n-1)\left(\tfrac{\gamma}{2b+\gamma}\right)\bar{q}, \quad \textit{always.}$$

$$q_{10} = \begin{cases} 0, & \textit{in the exclusive region,,} \\ (1-\alpha)Q_L^* + \alpha Q_H^* - (n-1)\left(\tfrac{\gamma}{2b+\gamma}\right)\bar{q}, & \textit{otherwise.} \end{cases}$$

$$q_{00} = \begin{cases} 0, & \textit{in exclusive and intermediate regions,} \\ Q_L^* - (n-1)\left(\tfrac{\gamma}{2b+\gamma}\right)\bar{q}, & \textit{in the full participation region.} \end{cases}$$

3.3 The Fully Distributed (FD) Coordination Structure

Under the FD regime, DR are decentralized to the branches and, in addition to its local information (x_i, ℓ_i), each branch i also knows the values of x_j for all $j \neq i$. This corresponds to the sharing of all communicable data among the branches.

Each branch's decisions are a function of its own (x_i, ℓ_i) and K_n, the number of branches having $x_i = 1$. Let $q_{x\ell}(k)$ denote the quantity decision for a branch having local datum x and local signal ℓ when $K_n = k$. As in the decentralized CS, at the optimum $q_{01}(k) = q_{00}(k)$ for all k. Define

$$k_{1,FD}^* = \left\lceil \left(\tfrac{4b}{\gamma}\right)\left(\tfrac{Q_L^*}{Q_H^* - Q_L^*}\right) \right\rceil, \text{ and}$$

$$k_{2,FD}^* = \begin{cases} \left\lceil \frac{4b[\alpha Q_H^* + (1-\alpha)Q_L^*] + \gamma(Q_H^* + Q_L^*)}{\gamma(1-2\alpha)(Q_H^* - Q_L^*)} \right\rceil, & \text{if } \alpha < \frac{1}{2} \\ +\infty, & \text{if } \alpha = \frac{1}{2} \end{cases}$$

Note that $k^*_{1,FD} \leq k^*_{2,FD}$. The equilibrium is fully participating when $k < k^*_{1,FD}$ and $b > 0$, or $k = 0$ and $b = 0$; exclusive when $k \geq k^*_{2,FD}$, and intermediate for the remaining values of k. Define

$$\bar{Q}(k) = \begin{cases} \frac{(2b+\gamma)k}{4b+(k+1)\gamma} \cdot [\alpha Q^*_L + (1-\alpha)Q^*_H], & \text{in the exclusive region,} \\ \frac{k(2b+\gamma)}{2(2b+k\gamma)} \cdot (Q^*_L + Q^*_H), & \text{in the intermediate region,} \\ \frac{2b+\gamma}{2b+n\gamma} \cdot [(n - \frac{k}{2})Q^*_L + \frac{k}{2}Q^*_H], & \text{in the full participation region,} \end{cases}$$

where $\bar{Q}(k)$ is the total expected quantity that the firm will produce given that $K_n = k$. The following Theorem provides the optimal quantities conditional on K_n.

Theorem 4 *: The optimal quantities under the FD regime when $K_n = k$ are given by:*

Case 1: If $k = 0$, then $q_{00}(0) = \left(\frac{2b+\gamma}{2b+n\gamma}\right) Q^*_L$.

Case 2: If $k \geq 1$,

$$q_{11}(k) = \begin{cases} \frac{2}{k}\bar{Q}(k), & \textit{in the exclusive region} \\ [\alpha Q^*_L + (1-\alpha)Q^*_H] - \frac{(k-1)\gamma}{k(2b+\gamma)}\bar{Q}(k), & \textit{in the intermediate region} \\ [\alpha Q^*_L + (1-\alpha)Q^*_H] + \frac{\gamma}{2b}\left[\frac{Q^*_L+Q^*_H}{2} - \bar{Q}(k)\right], & \textit{otherwise.} \end{cases}$$

$$q_{10}(k) = \begin{cases} 0, & \textit{in the exclusive region} \\ [(1-\alpha)Q^*_L + \alpha Q^*_H] - \frac{(k-1)\gamma}{k(2b+\gamma)}\bar{Q}(k), & \textit{in the intermediate region} \\ [(1-\alpha)Q^*_L + \alpha Q^*_H] + \frac{\gamma}{2b}\left[\frac{Q^*_L+Q^*_H}{2} - \bar{Q}(k)\right], & \textit{otherwise.} \end{cases}$$

$$q_{01}(k) = q_{00}(k) = \begin{cases} 0, & \textit{in the exclusive/intermediate regions,} \\ Q^*_L + \frac{\gamma}{2b}\left[Q^*_L - \bar{Q}(k)\right], & \textit{otherwise.} \end{cases}$$

Here, the information available to individual branches on the firm's other markets is summarized by K_n, the number of markets with favorable data. If K_n is sufficiently large, then only the branches with the most favorable demand information ($x_i = L_i = 1$) should receive positive quantities. For intermediate values of K_n, other branches with less favorable information also contribute. It is only when K_n is small, corresponding to a market-wide slump in demand, that quantities are shipped to the low-demand markets. This distribution of quantities is achieved by implicit coordination, without the explicit guidance of a central authority.

3.4 The No Information System (NI) Coordination Structure

Here, branches base their decisions solely on their local knowledge L_i, as they don't have an IS in place to record even their own data (the x_i's). Let q_ℓ denote the quantity decision for a branch with local signal $L_i = \ell$. Parameter values that satisfy the inequality $\frac{(1-\alpha t)Q^*_L + \alpha t Q^*_H}{(1-(1-\alpha)t)Q^*_L + (1-\alpha)tQ^*_H} \leq \frac{(n-1)\gamma}{4b+(n+1)\gamma}$

constitute the exclusive region, where q_1 is positive but $q_0 = 0$. For all other parameter values, the optimal solution is full participation. Define $\bar{q}$ as the expected quantity ordered by a branch prior to receiving any information. Then

$$\bar{q} = \begin{cases} \frac{2b+\gamma}{4b+(n-1)\gamma} \cdot [(1-(1-\alpha)t)Q_L^* + (1-\alpha)tQ_H^*], & \text{in the exclusive region,} \\ \frac{2b+\gamma}{2(2b+n\gamma)}((2-t)Q_L^* + tQ_H^*), & \text{in the full participation region.} \end{cases}$$

The following Theorem gives the equilibrium quantities q_ℓ in the different regions.

Theorem 5 : *The quantities ordered under the NI regime are as follows:*

$$q_1 = (1-(1-\alpha)t)Q_L^* + (1-\alpha)tQ_H^* - (n-1)(\tfrac{\gamma}{2b+\gamma})\bar{q}, \quad \textit{always}.$$

$$q_0 = \begin{cases} 0, & \textit{in the exclusive region,} \\ (1-\alpha t)Q_L^* + \alpha tQ_H^* - (n-1)(\frac{\gamma}{2b+\gamma})\bar{q}, & \textit{otherwise.} \end{cases}$$

We next turn to a comparison of the performance of alternative CS.

3.5 Profit Comparisons: Limiting Profits

We first compare the performance of our CS when the number of branches n is large. This case is analytically tractable and gives a number of interesting insights. It is followed by a numerical example that illustrates the behavior of profits under the different CS for small n. The numerical results further indicate that the limits well-approximate the actual profits even for moderate values of n.

Theorem 6 (Limiting Profits) : *As the number of branches n tends to ∞, the expected profits for each of our CS are as follows:*

(i)Centralized CS: $\Pi_C = \frac{1}{2} \cdot \left(\frac{(2b+\gamma)^2}{\gamma}\right)\left(\frac{Q_L^*+Q_H^*}{2}\right)^2$;

(ii)Decentralized and Fully-Distributed CS: $\Pi_D = \Pi_{FD} = \frac{1}{2} \cdot \left(\frac{(2b+\gamma)^2}{\gamma}\right)(\alpha Q_L^* + (1-\alpha)Q_H^*)^2$;

(iii)No Information System CS: $\Pi_{NI} = \frac{1}{2} \cdot \left(\frac{(2b+\gamma)^2}{\gamma}\right)((1-(1-\alpha)t)Q_L^* + (1-\alpha)tQ_H^*)^2$.

For a sufficiently large number of branches, the D coordination structure strictly outperforms C, irrespective of the values of t and α (as long as $\alpha < \frac{1}{2}$, i.e., the local signal is not pure noise). If the local signal is sufficiently precise that $(1-\alpha)t > \frac{1}{2}$, even NI dominates C in the limit; this relation is reversed, however, if the inequality is reversed. D does always strictly better than NI.

As $n \to \infty$, there is no performance gap between D and FD, i.e., the value of coordination (VOC) tends to zero. To understand the intuition behind this result, observe that under D, a branch need not accurately estimate the actions of every other branch, but only their *average effect*. The more accurately branches can estimate the total quantity ordered by all the others, the closer the firm's performance to that of the FD coordination structure, and in the limit, VOC tends to zero. Thus, statistical pooling effects work in favor of the D coordination structure, which outperforms C and approaches the performance of FD for large n.

One implication is that distributed IS add more value to firms operating in a small number of markets than to those operating in many markets (the increasing costs of distributed IS as the number of branches increases reinforce this effect). One case that is often touted as an example of the use of POS data to support fast response is Benetton [2, 3]. However, a closer examination [4] revealed that Benetton's retail operations were surprisingly low-tech and only a small fraction of the stores used POS at all; furthermore, Benetton had no intention of changing this. Given its 7,000 stores, diverse international operations and numerous design combinations, specific knowledge is clearly important for Benetton's sales. Benetton may well find a decentralized system not involving instantaneous data-sharing sufficient because of statistical pooling effects.

To understand why D does better than C when n is large, observe that, for both CS, the shipment quantities to each market are a function of two estimates: *(i)* the demand in that market, and *(ii)* the *total* demand in all other markets (recall Theorem 1). The availability of both data and local knowledge enables D to do better than C on the first count, whereas for finite n C is superior to D on the second count because the data from *all* the markets are available to the center. As n grows, each branch under D estimates the total demand with increasing accuracy, and in the limit, it does as well as under C. However, D's advantage on the first count is never overcome by C, as the loss of local knowledge in C is iredeemable. Thus, for example, the inability of the centralized structure of Mrs. Fields Cookies [36] to successfully cope with a large number of diverse retail locations may well be attributed to the loss of local knowledge inherent in its CS.

The limiting profits for all four CS are decreasing and *convex* functions of α. Thus, profits increase as local knowledge becomes more precise; furthermore, there are increasing returns to increased local knowledge precision. This points again to the importance of improving and taking advantage of local knowledge, reflected in current retailing practice [14]. Indeed, successful companies such as Wal-Mart, Toys "R" Us and J.C. Penney are now giving their store managers more decision-making authority to take advantage of their local knowledge.

Unlike the VOC, the value of Information Systems ($VOIS = \Pi_D - \Pi_{NI}$) does *not* converge to 0 as the number of branches increases. In the limit, the VOIS approaches

$$\frac{1}{2}\left(\frac{(2b-\gamma)^2}{\gamma}\right)\cdot\left[\{(1-\alpha)Q_H^* + \alpha Q_L^*\}^2 - \{(1-\alpha)tQ_H^* + (1-(1-\alpha)t)Q_L^*\}^2\right],$$

which is strictly positive and decreases with α, i.e., increases with precision in local knowledge. The important insight is that knowledge and data need not be substitutes, and they may well be complements: with better local knowledge, the value of local data also increases. This result, however, depends on the assumed structure of the demand shocks: under the alternative model specification with $s_i = \max\{x_i, y_i\}$) (see Section 2.4), data and local knowledge become substitutes. Thus, the actual relation between data and local knowledge depends on specific circumstances.

It is interesting to note that our results are qualitatively different from those obtained under the MR [31, Ch.6] model, where the expected profits are asymptotically linear in n and hence, unbounded. This reflects the increasing "arbitrage" profits as n increases, something which is impossible in our model (and in the retailing context). Further, while under the MR model, VOC tends to *infinity* as $n \to \infty$, its limit is *zero* in our model.

3.6 Numerical Example

We compare the profitability of the alternative CS for a representative example. The parameter settings for the example are $t = \frac{1}{2}, a_H = 60, a_L = 24, c = 20, \gamma = 2$ and $b = 1$; these imply $Q_H^* = 10$ and $Q_L^* = 1$. We examine three levels of the local signal imprecision: $\alpha = 0$, 0.3 and 0.5 (precise, intermediate and no information, respectively).

Figures $2(a)$–$2(c)$ show firm profits under our CS as a function of the number of branches n for different values of α. For $\alpha = 0$ (Figure $2(a)$), the FD and D regimes do very well, exploiting the highly reliable local signal. The profits under both approach a limit that corresponds to full information (i.e., full knowledge of the state of each market). The performance of C is independent of α, and in the limit for large n, profits are about 30% of the FD and D limits. The NI regime is the worst performer, but it approaches the performance of C as n increases.

For $\alpha = 0.3$, Figure $2(b)$ shows a significant drop in profits under both FD and D. However, the value of local knowledge is still sufficient for D to dominate C. When $\alpha = 0.5$ (Figure $2(c)$), there is no specific knowledge to exploit. The C regime does consistently better than D, and its performance is identical to that of FD: absent useful local knowledge, data sharing with decentralized decision making is equivalent to centralization (in this case, centralized systems are likely to be adopted for cost reasons). In all cases, the NI regime performs poorly. As n increases, the actual expected profits approach the limiting profits of Theorem 6 fairly quickly. For example, for $\alpha = 0.3$ and $n = 100$, the percentages of the limiting profits obtained, respectively, under the C, D, FD and NI regimes are 98.0%, 93.5%, 94.3% and 97.1%.

Figure 3 shows the VOC for our three values of α. In the decentralized CS, there is a shift from the full participation region to the intermediate region and then to the exclusive region, as n increases. In the FD regime, as n increases, K_n probabilistically takes higher values, and so the exclusive region begins to dominate. In all three cases, VOC first increases with n and then falls. Intuitively, there are two opposite forces affecting VOC. On the one hand, the firm's scale increases with the number of branches, which makes coordination more valuable and drives VOC up. On the other hand, the statistical pooling effect discussed in the previous section gets more accurate as n increases, and tends to reduce the value of explicit coordination. For very small values of n, the first force predominates. Beyond a critical value of n, the change in scale as n increases is less of a factor, and the increased accuracy of 'implicit' coordination reduces the VOC. For example, when $n = 100$ branches and $\alpha = 0.3$, the VOC is just 0.89% of the decentralized CS profits, that is, the additional profits in switching from D to FD are less than 1%.

Figure 4 shows that VOIS is sizable (IS do have value after all!) and increases with the number of branches at a decreasing rate, as might be expected. The VOIS is *higher* when α is *lower*, showing that knowledge and data are complements (as they are in the limit; recall Theorem 6). The lesson is that finely honed instincts on a specific market need not *ipso facto* diminish the value of IS, depending on the structure of the demand shocks (also see Section 2.4).

We performed the analysis with identical parameter values for the case of perfectly elastic demand ($b = 0$). The results (available upon request) were similar to those in Figures 2–4, with faster convergence to the limits of Theorem 6.

4 Incentive Issues

So far, we assumed that the branches act as a team, i.e., their common objective is to maximize the firm's overall expected profits. In practice, divisional (or branch) managers are often evaluated on their division's performance rather than the entire firm's. This leads to incentive problems in the CS with decentralized decision rights (D,FD and NI: see Figure 1). In this section, we consider transfer-pricing schemes that address these incentive conflicts.

4.1 Optimal Transfer Pricing

Our first transfer pricing scheme is based on the Clarke-Groves-Loeb mechanism (cf. [9, 20, 21]) of public economics: if branch i receives q_i and the total quantity received by the other branches is Q_{-i}, then i pays

$$TC(Q_{-i} + q_i) - TC(Q_{-i}), \tag{2}$$

where $Q_{-i} = \sum_{j \neq i} q_j$. In (2), $TC(Q_{-i} + q_i)$ is the firm's production cost *with* i's order and $TC(Q_{-i})$ is the production cost if branch i ordered nothing. Thus, branch i pays the incremental cost of its order, taking the quantities produced for all other branches as given. This transfer price forces i to internalize the cost that its order imposes on the rest of the firm. The optimality of this transfer-pricing scheme is proved in the following Theorem.

Theorem 7 (Optimal Transfer Pricing) : *When the firm employs the transfer pricing scheme (2) and each branch maximizes its own expected profits, the quantities ordered by each branch will constitute a (Bayesian) equilibrium if and only if they solve the team decision problem.*

Theorem 7 shows that scheme (2) solves the incentive problem and results in all decision points operating as if they were a team. Intuitively, under this scheme each branch's expected marginal cost for its order is equal to the expected incremental cost the order inflicts on the firm, where both expectations are taken with respect to the branch's available information. Thus, the quantities ordered under (2) will be identical to those ordered by a team.

Under this scheme, however, the price charged to a branch depends on all other branches' orders. Consequently, at the time of ordering, a branch does not know the actual price it will pay. This is uncommon in practice. We thus consider *determinate* transfer pricing schemes which charge each branch according to a pre-specified function of its order quantities, independent of other branches' orders. Such determinate schemes are easier to implement, but they may give rise to *agency costs.*

4.2 Determinate Transfer Pricing Schemes

A *determinate* transfer pricing scheme operates as follows: The center offers a fixed (deterministic) price schedule, specifying the dependence of each branch's order cost on its *own* order quantities. The branches receive their information (the Ψ_i's) and then decide on their expected profit-maximizing order quantities, taking the transfer price into account. The center wants to maximize expected firm profits, indirectly taking advantage of the local knowledge of the branches. Thus, the optimal price schedule should anticipate both the information received by the branches and their reactions. The following Theorem shows that for all three decentralized CS (D, NI and FD), there are quadratic determinate pricing schemes that are optimal.

Theorem 8 (Optimal Determinate Pricing for D, NI and FD) *(i) Under D, an optimal determinate transfer pricing schedule is the quadratic function* $A_D \cdot q_i + B_D \cdot q_i^2$, *where* $A_D = c + \gamma(n-1)\left[tq_{00} + (\frac{1-t}{2})(q_{10}+q_{11})\right]$, $B_D = \frac{1}{2}\gamma$, *and* q_{00}, q_{10} *and* q_{11} *are the quantities derived in Theorem 3. This scheme implements the team solution for the D regime with no agency costs.*

(ii) Under NI, an optimal determinate transfer pricing schedule is the quadratic function $A_{NI} \cdot q_i + B_{NI} \cdot q_i^2$, *where* $A_{NI} = c + \gamma(n-1)\left[\frac{q_0+q_1}{2}\right]$, $B_{NI} = \frac{1}{2}\gamma$, *and* q_0 *and* q_1 *are the quantities derived in Theorem 5. This scheme implements the team solution for the NI regime with no agency costs.*

(iii) Under FD, the optimal determinate transfer pricing schedule is the same as for D. With this transfer pricing scheme, the firm's expected profits under FD and D are identical.

Recall that under FD, branches know the value of K_n, the number of branches with $x_i = 1$. The center would like to design its pricing schedule so as to induce the branches to make use of this knowledge in placing their orders. Theorem 8 tells us that the center cannot do so – in fact, when objectives diverge, the shared data (captured by K_n) is useless, and the FD structure does no better than D. Theorem 8 also implies that under determinate transfer pricing, the agency costs for FD are equal to the VOC derived for the team problem. One implication is that for comparable decentralized firms, ownership of their outlets is more conducive to the use of distributed IS than (say) the use of franchises, since franchisees are more likely to be self-maximizers than team-players. Furthermore, as the number of outlets becomes large, the benefits of the additional information provided in FD (over D) fall, and the agency costs in FD fall correspondingly. Both the informational benefits and the agency costs of FD tend to 0 as n tends to infinity.

5 Correlated Demands: Aggregate Shocks

So far, we assumed that markets were statistically independent. In practice, the demand across markets could be correlated because of common macroeconomic factors, consumer preferences or product features whose effects are not perfectly known until demand is realized. Further, while branches are likely to have superior knowledge of their local circumstances, the center may be in a better position to make judgments on such market-wide effects.

To model these phenomena, we assume that the state of each market i is given by $s_i = z \cdot x_i \cdot y_i$, where x_i and y_i (as well as the local signals L_i) are as in Section 2. The aggregate shock z is 0 or 1 with equal prior probabilities, and it can be imperfectly observed by the center through a signal M satisfying $M = z$ with probability $(1 - \beta)$ and $M = 1 - z$ with probability β, where $\beta \leq \frac{1}{2}$. This observation constitutes specific knowledge which is available to decision-makers at the center and cannot be communicated to the branches.

This model has two distinct purposes. First, it serves to analyze the sensitivity of our key results to the assumption that demands are independent across markets. Second, it adds a strong element of *central* specific knowledge that can provide another reason for centralization. The central specific knowledge posited here is quite powerful, as the center is assumed to have exclusive access to the signal M and it can make an inference about the aggregate shock z that affects *all* the markets. Further, when the aggregate shock is low ($z = 0$), it determines the states of all markets regardless of their local circumstances.

The solutions obtained for this model under our alternative CS are similar in structure to those derived in Section 3. A succinct comparison among the different CS is obtained by considering the limiting profits as $n \to \infty$ under each structure, analogous to Theorem 6.

Theorem 9 (Limiting Profits under Correlated Demand) : *As the number of branches n tends to ∞, the expected profits for each of our CS are as given below:*

(i) Centralized CS: $\Pi_C = \frac{1}{2} \cdot \left(\frac{(2b+\gamma)^2}{\gamma}\right) \left\{ \frac{\left((1-\frac{\beta}{2})Q_L^* + (\frac{\beta}{2})Q_H^*\right)^2}{2} + \frac{\left((\frac{1+\beta}{2})Q_L^* + (\frac{1-\beta}{2})Q_H^*\right)^2}{2} \right\}$;

(ii) Decentralized and Fully-Distributed CS: $\Pi_D = \Pi_{FD} = \frac{1}{2} \cdot \left(\frac{(2b+\gamma)^2}{\gamma}\right) \left((\frac{1+\alpha}{2})Q_L^* + (\frac{1-\alpha}{2})Q_H^*\right)^2$;

(iii) No Information System CS: $\Pi_{NI} = \frac{1}{2} \cdot \left(\frac{(2b+\gamma)^2}{\gamma}\right) \left((1 - \frac{(1-\alpha)t}{2})Q_L^* + \frac{(1-\alpha)t}{2} Q_H^*\right)^2$.

Starting with the first objective of Theorem 9 (sensitivity analysis), part (*ii*) illustrates the insensitivity of our result that the limiting VOC is zero to the independence assumption: as $n \to \infty$, the expected profits under D converge to those under FD even in the presence of an aggregate shock. In addition, the limiting VOIS is positive for all α, as in Section 3. Further, the VOIS is a decreasing function of α, confirming that data and local knowledge are complements regardless of the existence of an aggregate shock (this specific result, however, is sensitive to the multiplicative model assumption; see Section 3). In particular, when $\beta = \frac{1}{2}$, the qualitative results are substantively the same as in Section 3.

As for our second objective, Theorem 9 enables us to study the impact of specific central knowledge such as the deep understanding of fashion trends, the untransferable instincts of central buyers and their intuition regarding global factors that apply to all markets. As expected, this makes the C regime, which enables the firm to take advantage of such knowledge, more attractive. In particular, when the central specific knowledge is accurate (modeled here by low β) and the local specific knowledge is not (α is close to $\frac{1}{2}$), the C regime gives rise to higher profits than D/FD. Thus, for example, according to The Gap's CEO, its central buyers have a better understanding of market trends than store managers do, and local demand factors are less important than the ability to forecast the national market. As a result, central buyers (each specializing in a product line) make the stocking and pricing decisions for virtually all stores using comprehensive data obtained from the stores' POS systems. These decisions are partly automated (i.e., based on the *data* from all branches) and partly based on the the buyers' intuition and knowledge (modeled here by the signal M). The relative unimportance of unquantifiable local demand factors is probably due to the fact that The Gap markets relatively homogeneous apparel compared to many other retailers.

We further note that in the limit, the *data* plays no role in the comparison between the decentralized (D/FD) and C regimes: it is explicitly available under both C and FD, and (by part (*ii*) of Theorem 9) it can be effectively inferred under D, just as in our earlier model. Thus, the comparison is driven by the precisions of the local and central elements of specific knowledge, and Theorem 9 enables us to quantify the tradeoff between them.

The profits under D/FD are greater than or equal to those under C if and only if

$$\frac{Q_L^*}{Q_H^*} - \frac{\left(\frac{1}{2}-\beta\right)^2 - (\frac{1}{2}-\alpha)(\frac{3}{2}-\alpha)}{\left(\frac{1}{2}-\beta\right)^2 + (\frac{1}{2}-\alpha)(\frac{5}{2}+\alpha)} \geq 0. \tag{3}$$

The left hand side of (3) is an increasing function of β and a decreasing function of α, as expected: more precise local knowledge makes the D/FD regime more attractive, and more precise central knowledge has the opposite effect. When $\alpha = \beta = \frac{1}{2}$, (3) is not well-defined. In this case, all three regimes yield identical profits $\Pi_C = \Pi_D = \Pi_{FD} = \frac{1}{2} \cdot \left(\frac{(2b+\gamma)^2}{\gamma}\right)\left((\frac{3}{4})Q_L^* + (\frac{1}{4})Q_H^*\right)^2$, as might be expected since both the central and local specific knowledge are pure noise.

When the central and local specific knowledge have the same precision but are not pure noise ($\alpha = \beta \neq \frac{1}{2}$), condition (3) implies that D/FD will always dominate C. More generally, for any given value of $\frac{Q_L^*}{Q_H^*}$, we can divide the square $[0, \frac{1}{2}] \times [0, \frac{1}{2}]$ in the (α, β) plane into a region where C dominates and a region where D/FD dominate; this was done in Figure 5 for $\frac{Q_L^*}{Q_H^*} = 0.1, 0.25$ and 0.5. The C regime is preferable only in the right-hand bottom region of the square (corresponding to low values of β and high values of α), which shrinks as the ratio $\frac{Q_L^*}{Q_H^*}$ increases. Thus, for example, as long as $\frac{Q_L^*}{Q_H^*} > 0.1$ and $\alpha < 0.34$, the D/FD regimes dominate *for all* β, even if the central specific knowledge is perfect. The corresponding α threshold when $\frac{Q_L^*}{Q_H^*} = \frac{1}{2}$ is 0.45. As shown in Figure 5, for other values of $\frac{Q_L^*}{Q_H^*}$, the local specific knowledge has to be rather inaccurate, and the central specific knowledge – sufficiently precise, for the C regime to be preferable. These results illustrate the power of decentralization [24] while also quantifying some of its limits.

6 Concluding Remarks

Information Technology is a key enabler of the ongoing rethinking and radical redesign of firms' business models [23]. However, with the exception of a few widely-replicated templates, the principles that should guide the redesign process are still unclear. We believe that an important part of the answer lies in the analysis of firms' CS. The design of organizations requires an analysis of what kinds of information the firm needs to acquire, alternative ways of distributing this informational endowment and ways of structuring the organization to match its information structure. Key to this analysis is the recognition that the firm's organizational structure and its IS must be co-determined, and that varying one while leaving the other fixed is likely to lead to suboptimal results.

In this paper we proposed a theoretical framework for analyzing firms' CS and applied it to a firm that faces demand uncertainty in multiple horizontal markets. We studied the impact of alternative CS on firm performance. The results provide insights to the process by which IS produce value to a firm, and the factors that affect this value. We characterized conditions that favor a more centralized system and those that favor greater decentralization. We defined the value of coordination and the value of IS and studied their behavior. We found that even in the absence of explicit coordination, each branch can sometimes properly anticipate the net effect of the actions of all the other branches using statistical averaging. When this happens, the value of coordination tends to zero and fully-distributed systems are unnecessary. We also showed that knowledge and data are actually complements under our model specification.

We studied alternative models, showing where key results are sensitive to model specification and where they are not. The VOC tends to zero for a large number of branches and the VOIS is positive for all the models studied. The complementarity between data and specific knowledge holds in a model with correlated demands but depends on the assumption of multiplicative shocks. The dominance of the decentralized CS for a large number of branches is not sensitive to the multiplicative shock assumption. When the center has exclusive knowledge of a signal on an aggregate shock, the centralized CS may prevail, but this happens only when the local signal is sufficiently inaccurate in *absolute* terms (as well as relative to the central signal). In fact, there is a wide range of parameter values for which even perfect knowledge of the aggregate shock is insufficient compensation for the loss of local knowledge under centralization.

Future work could explore other modeling choices that build on our model structure. For example, x_i and y_i could be modeled as separate estimators (with possibly different efficiencies) of the demand state s_i. The state would no longer be binary-valued, but the added richness might well compensate for the greater analytical complexity. In our models (including the one with aggregate shocks), decision points shared data to learn more about their marginal costs, but not about their own demand. Branches could actually learn about their own market demand from other branches' data. This could be studied using a different model of aggregate shocks, where data (such as store sales measured by POS systems) partially captures aggregate shocks in addition to local variations and the center serves as a statistical aggregator of the data.

One of the key themes of our analysis is the importance of co-locating knowledge and the power to make decisions using that knowledge. We found that for firms operating in multiple markets, there are increasing returns to any process that increases (or taps into) local knowledge. In retailing, firms have first focussed on centralization but are now recognizing that local knowledge is indispensable. A recent *Economist* survey echoes these conclusions: "Initially, computers shifted many management functions – such as buying and pricing – away from the shop and towards the centre... But centralising everything risks ignoring the peculiarities of local taste that can make or break a particular store. Some retailers are now customising their computer systems, allowing each store to set its prices and adjust its assortment according to local conditions... The best way to run a retail chain... is to operate every store differently, with locally-tailored ranges and prices." [14].

Our analysis builds on the JM [26] approach to the study of organizations. Commenting on this approach, Demsetz [12] points out that "... their discussion... marks only the beginning of the analysis [of organizational design]... they take the distribution of knowledge in a business organization as a given when, in fact, it is not. The distribution of knowledge within a firm is endogenous... The 'firm' *decides* what knowledge to acquire."

In terms of our model, Demsetz's point is that both the informational endowment of the firm and its allocation among decision points should be endogenous. Our model focusses on the second extension proposed by Demsetz: the *distribution* of the informational endowment within the firm is endogenous. The endogeneity of the initial informational endowment is only partially captured by the firm's choice of CS. In the NI coordination structure, market data are not available, while in the other CS, the firm *chooses* to acquire the data $\{x_i\}_{i=1}^n$. Future work could expand the model to focus on the choice of data, and knowledge, to be captured. Future work could also study the *costs* of alternative coordination structures and incorporate them in the analysis. Another promising direction is a more detailed study of incentive issues, especially the relationship between the choice of CS and agency problems.

A more direct extension of the model is to a multiperiod setting. In addition to information, inventory can also be used to cope with demand uncertainty [35]. The study of the interplay of inventory and information, and their relationship to the firm's coordination structure, will hopefully provide additional insights.

References

[1] Aoki, M., "Horizontal vs. Vertical Information Structure of the Firm", *American Economic Review*, December 1986, v76, pp. 971-983.

[2] *Benetton (A)*. Harvard Business School Case, 9-685-014, 1984.

[3] *Benetton (B).* Harvard Business School Case. 9-685-020. 1985.

[4] *Benetton S.p.A. : Industrial Fashion (A).* Harvard Business School Case. 9-188-003. 1987.

[5] Bolton. P. and M.Dewatripont. "The Firm as a Communication Network". *The Quarterly Journal of Economics.* November 1994. v109n4. pp. 809-839.

[6] Bolton. P. and J.Farrell. "Decentralization. Duplication and Delay". *Journal of Political Economy.* August 1990. v98n4. pp. 803-826.

[7] Brynjolfsson. Erik and Haim Mendelson. "Information Systems and the Organization of Modern Enterprise", *Journal of Organizational Computing.* 1993. v3n3. pp. 245-255.

[8] Bull, Katherine,"Sell Smart, Sell More– Old-line merchandisers change IT strategies to not only survive, but to prosper", *Information Week,* September 18,1995.

[9] Clarke. E., "Multipart Pricing of Public Goods", *Public Choice.* 1971, v11, pp. 17-33.

[10] Cremer. J., "A Partial Theory of the Optimal Organization of a Bureaucracy", *Bell Journal of Economics,* Autumn 1980, pp. 683-693.

[11] Demarest. Marc,"Leading Edge Retail," *DBMS,* December 1994, v7n13, pp. 78-79.

[12] Demsetz, H., "Comments" [on reference [26] below] in: *Contract Economics,* Lars Werin and Hans Hijkander, eds., Cambridge, MA: Basil Blackwell. 1992, pp.275-281.

[13] *Dun's Business Month,* "The 5 Best-Managed Companies : Toys "R" Us: King of the Hill," Dec 1985, v126n6, pp. 40-41.

[14] *The Economist,* "Stores of Value", Survey: Retailing, p. 5, March 4, 1995.

[15] Fisher, M.L., J.H. Hammond, W.R. Obermeyer and A. Raman, "Making Supply Meet Demand in an Uncertain World", *Harvard Business Review,* May-June 1994, pp. 83-93.

[16] Frazier, R.M., "Quick Response in Soft Lines", *Discount Merchandiser,* January 1986, pp. 86-89.

[17] Geanakoplos, J. and P. Milgrom, "A Theory of Hierarchies Based on Limited Managerial Attention", *Journal of the Japanese and International Economies,* 1991. n5, pp. 205-225.

[18] Gilman, Hank, "J.C. Penney Decentralizes Its Purchasing", *The Wall Street Journal*, May 8, 1987.

[19] Gonsalvez, D., "Distribution in the Automotive Industry", GM Research & Development Center, 1994.

[20] Groves, T., "Incentives in Teams", *Econometrica*, 1973, v41, pp. 617-631.

[21] Groves, T. and M. Loeb, "Incentives and Public Inputs", *Journal of Public Economies*, 1975, v4, pp. 311-326.

[22] Gurbaxani, V. and S. Whang, "The Impact of Information Systems on Organizations and Markets", *Communications of the ACM*, 1991, v34n1, pp. 59-73.

[23] Hammer, M.C. and J. Champy, "*Reengineering the Corporation*", Harper Business, 1993.

[24] Hayek, F.A., "The Use of Knowledge in Society", *American Economic Review*. Sep. 1945, v35n4, pp. 1-18.

[25] Jensen, M.C. and W. Meckling,"Theory of the Firm: Managerial Behavior, Agency Costs and Ownership Structure", *Journal of Financial Economics*, 1976, v3, pp 305-360.

[26] Jensen, M.C. and W. Meckling, "Specific and General Knowledge, and Organizational Structure", in: *Contract Economics*, Lars Werin and Hans Hijkander, eds. Cambridge, MA: Basil Blackwell, 1992, pp.251-274.

[27] Malone, T.W. and K.G. Crowston, "The Interdisciplinary Study of Coordination", ACM Computing Surveys, March 1994, v26n1, pp. 87-119.

[28] Malone, T.W., and J.F.Rockart, "Computers, Networks, and the Corporation", *Scientific American*, September 1991, 265, 3, pp. 128-136.

[29] Mandell, Mel, "Kmart's $1 Billion Bar-Code Bet", *Computerworld*, Aug. 12, 1991, v25n32, p. 53,55.

[30] Marschak, J., "Elements for a Theory of Teams", *Management Science*, January 1955, v1n2, pp. 127-137.

[31] Marschak, J. and R. Radner, *Economic Theory of Teams*, 1972, New Haven, Yale University Press.

[32] Mayo, Ken, "Retailers: the heat is on," *Business Computer Systems*, Jan. 1986, v5n1, p. 48-50.

[33] Mendelson, Haim, *The Economics of Information Systems Management*, Manuscript, 1987–91.

[34] Mendelson, Haim, "MIS and the Economics of Organization," *Proceedings of the 22nd Hawaii International Conference on System Sciences*, Kona, Hawaii, 1989, Vol. III, pp. 87-88.

[35] Milgrom, Paul and John Roberts,"Communication and Inventory as Substitutes in Organization Production", *Scandinavian Journal of Economics*, 1988, v90n3, pp. 275-289.

[36] *Mrs. Fields' Cookies*. Harvard Business School Case 9-189-059 (rev. 1989).

[37] Radner, R., "Hierarchy: The Economics of Managing", *Journal of Economic Literature*, September 1992, v30, pp. 1382-1415.

[38] Radner, R., "The Organization of Decentralized Information Processing", *Econometrica*, September 1993, pp. 1109-1146.

[39] Stevenson, Mark, "The Store to End All Stores", *Canadian Business Review*, May 1994, v67n5, pp. 20-22.

[40] Van Zandt, T. and R. Radner, "Information Processing and Returns to Scale of a Statistical Decision Problem", *Working paper*, June 16, 1995.

[41] Varian, Hal R., *Microeconomic Analysis*, W.W.Norton & Company, New York, 1992.

[42] Wilson, Mark, "Point of Sale: Future Arrives Now for Retailers," *Calgary Herald*, December 28, 1994, p. D1.

FIGURE CAPTIONS

Figure 1: Coordination structures by decentralization of decision rights and information available.

Figure 2: Expected profits under alternative coordination structures as a function of the number of branches, n, for the numerical example of Section 3.6. The demand curves are downward-sloping with $b = 1$. The imprecision of the local signal takes on three values:

(*a*) $\alpha = 0$, corresponding to an error-free local signal;

(*b*) $\alpha = 0.3$; and

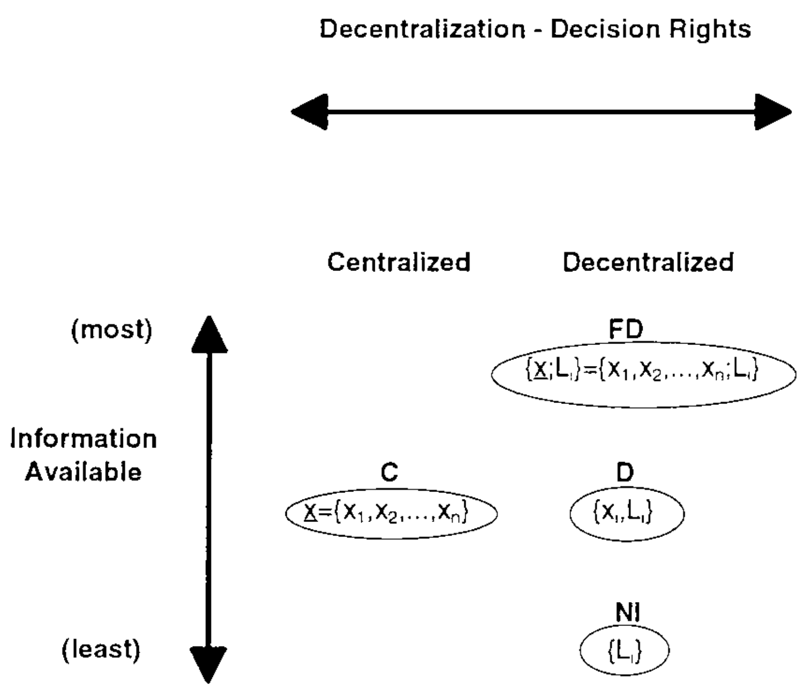
(*c*) $\alpha = 0.5$, corresponding to a non-informative local signal.

Figure 3: Value of Coordination as a function of the number of branches, n, for the numerical example of Section 3.6. The Value of Coordination is defined as the difference in expected profits between the Fully-Distributed and Decentralized coordination structures.

Figure 4: Value of Information Systems as a function of the number of branches, n, for the numerical example of Section 3.6. The Value of Information Systems is defined as the difference in expected profits between the Decentralized and "No Information" coordination structures.

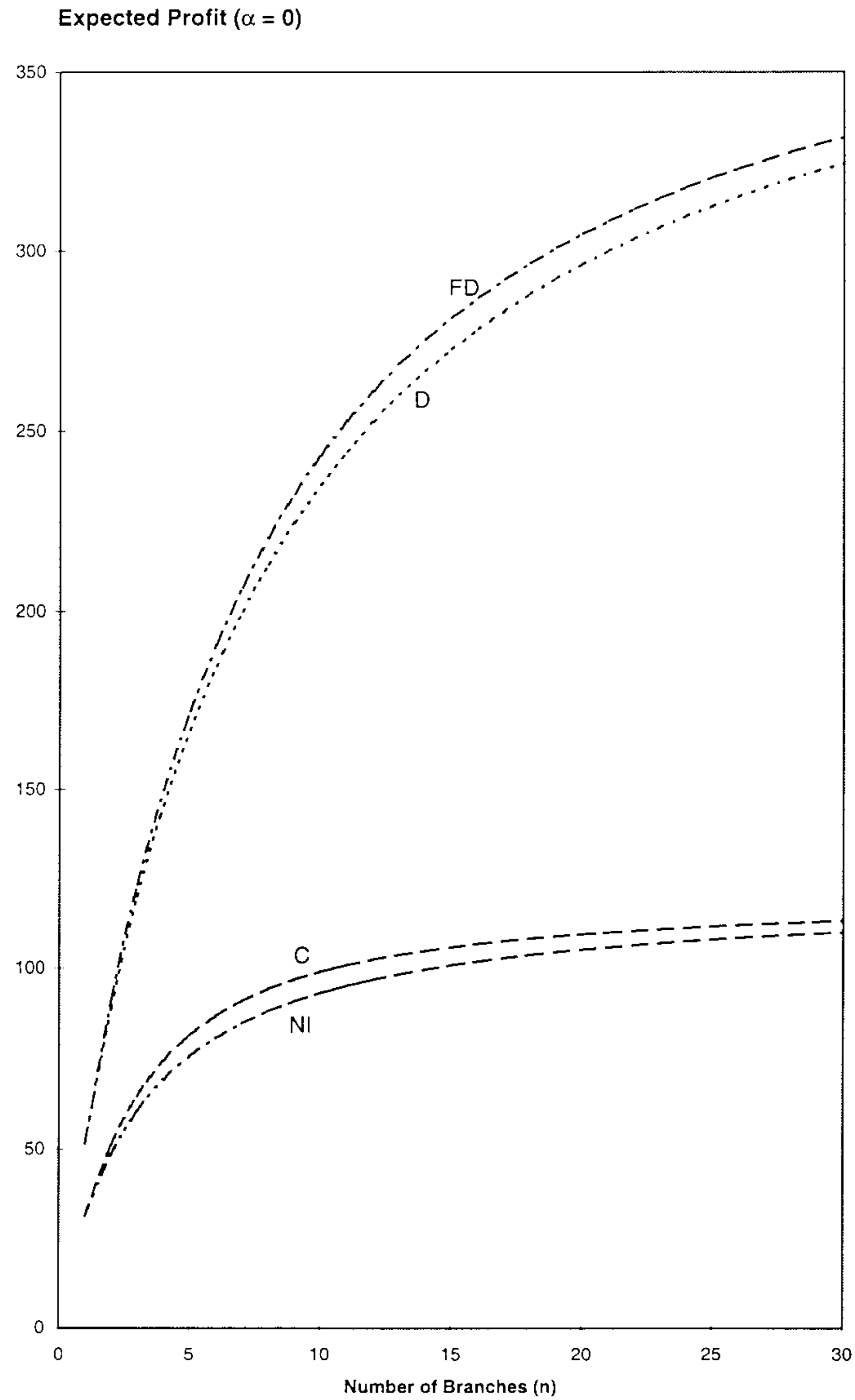
Figure 5: Indifference curves in the (α, β) plane between the Centralized and decentralized (D/FD) Coordination Structures for $\frac{Q_L^*}{Q_H^*} = 0.1, \frac{1}{4}$ and $\frac{1}{2}$. The D/FD regimes are preferable to C in the region above the corresponding curve.

Figure 1



Decentralization - Decision Rights
Centralized
Decentralized
(most)
Information Available
(least)
FD
$\{\underline{x};L_i\}=\{x_1,x_2,\ldots,x_n;L_i\}$
C
$\underline{x}=\{x_1,x_2,\ldots,x_n\}$
D
$\{x_i,L_i\}$
NI
$\{L_i\}$

Figure 2(a)



Expected Profit (α = 0)
350
300
250
200
150
100
50
0
FD
D
C
NI
0
5
10
15
20
25
30
Number of Branches (n)

Figure 2(b)

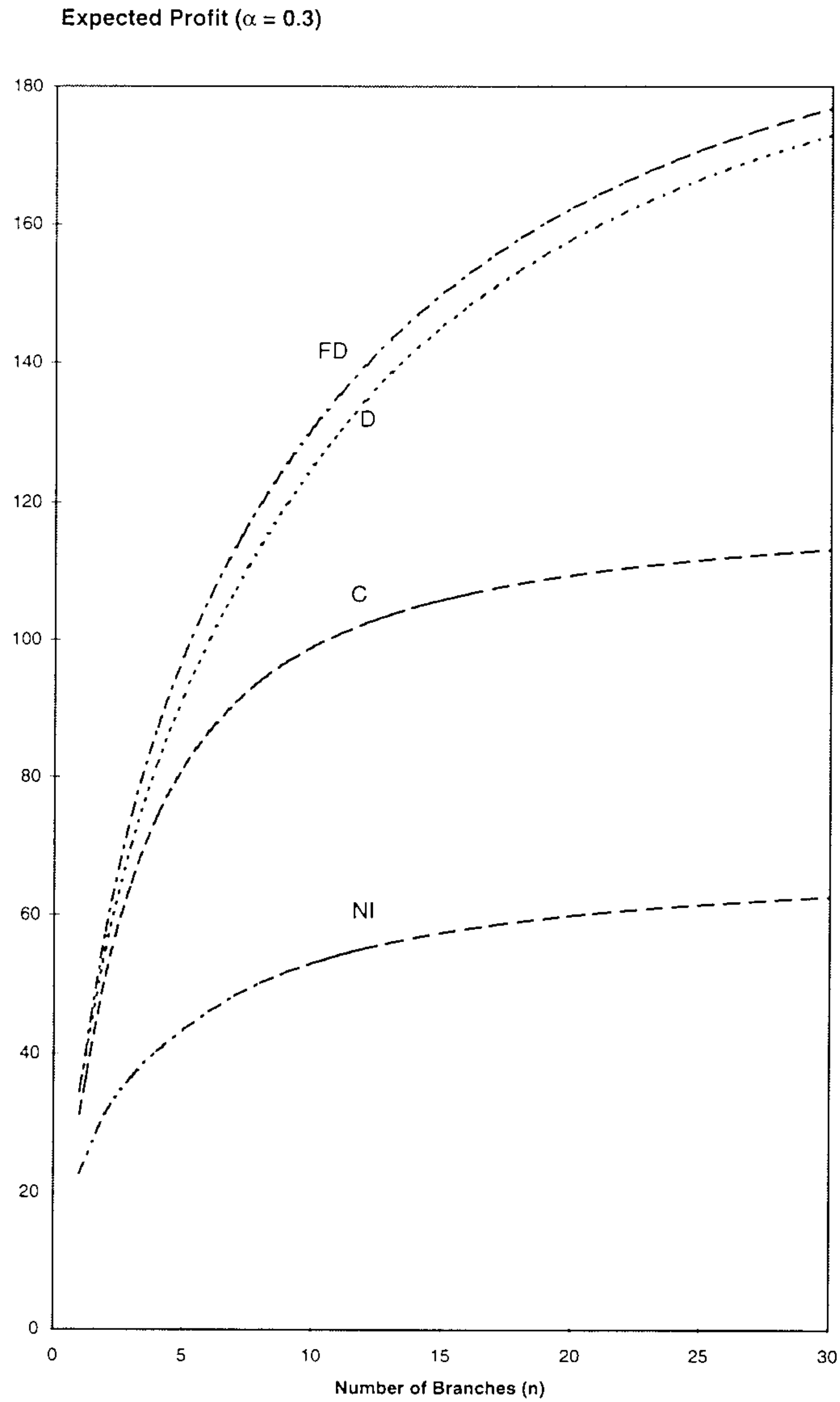

Expected Profit (α = 0.3)
180
160
140
120
100
80
60
40
20
0
0
5
10
15
20
25
30
FD
D
C
NI
Number of Branches (n)

Figure 2(c)

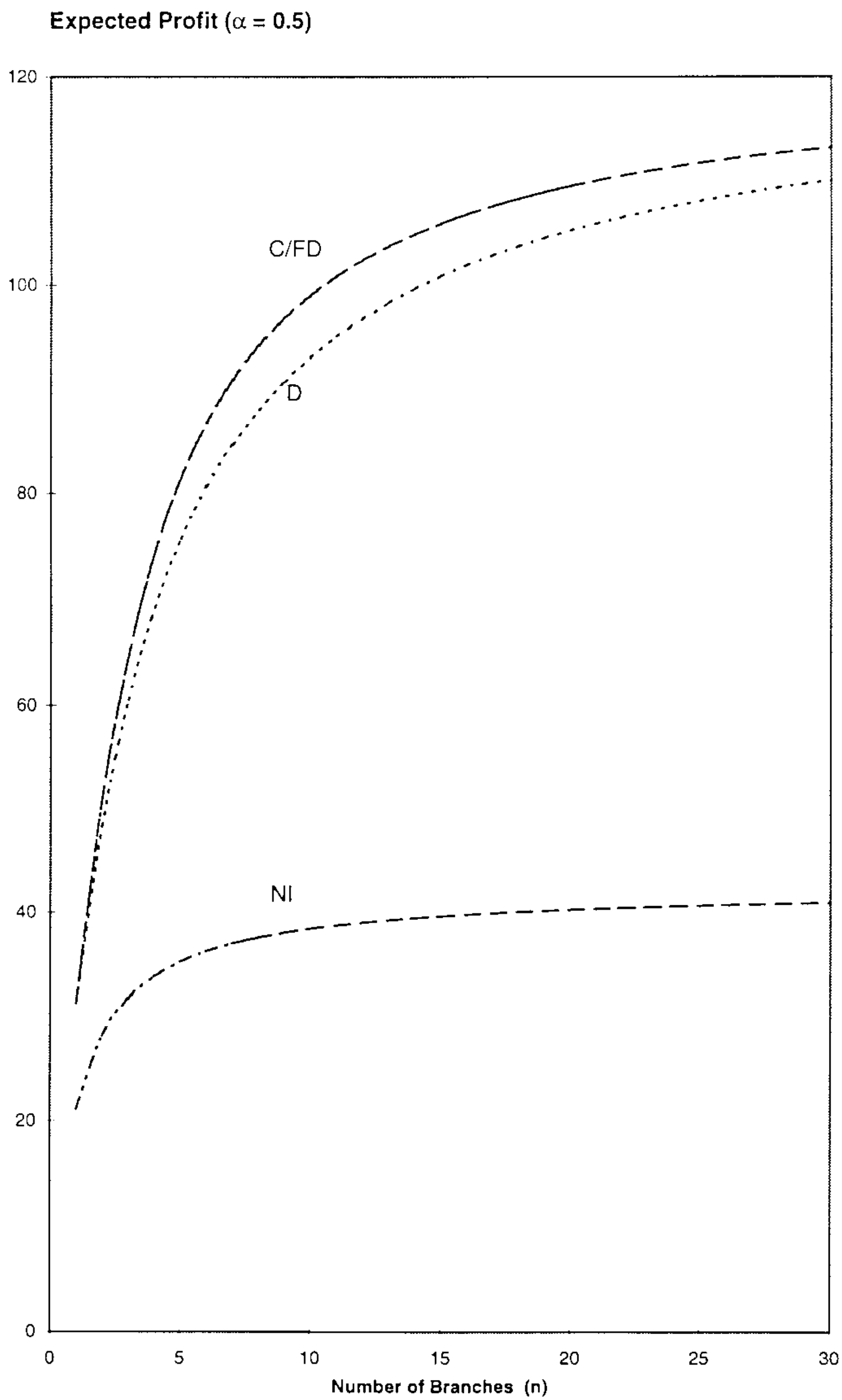

Expected Profit (α = 0.5)
120
100
80
60
40
20
0
0
5
10
15
20
25
30
Number of Branches (n)
C/FD
D
NI

Figure 3

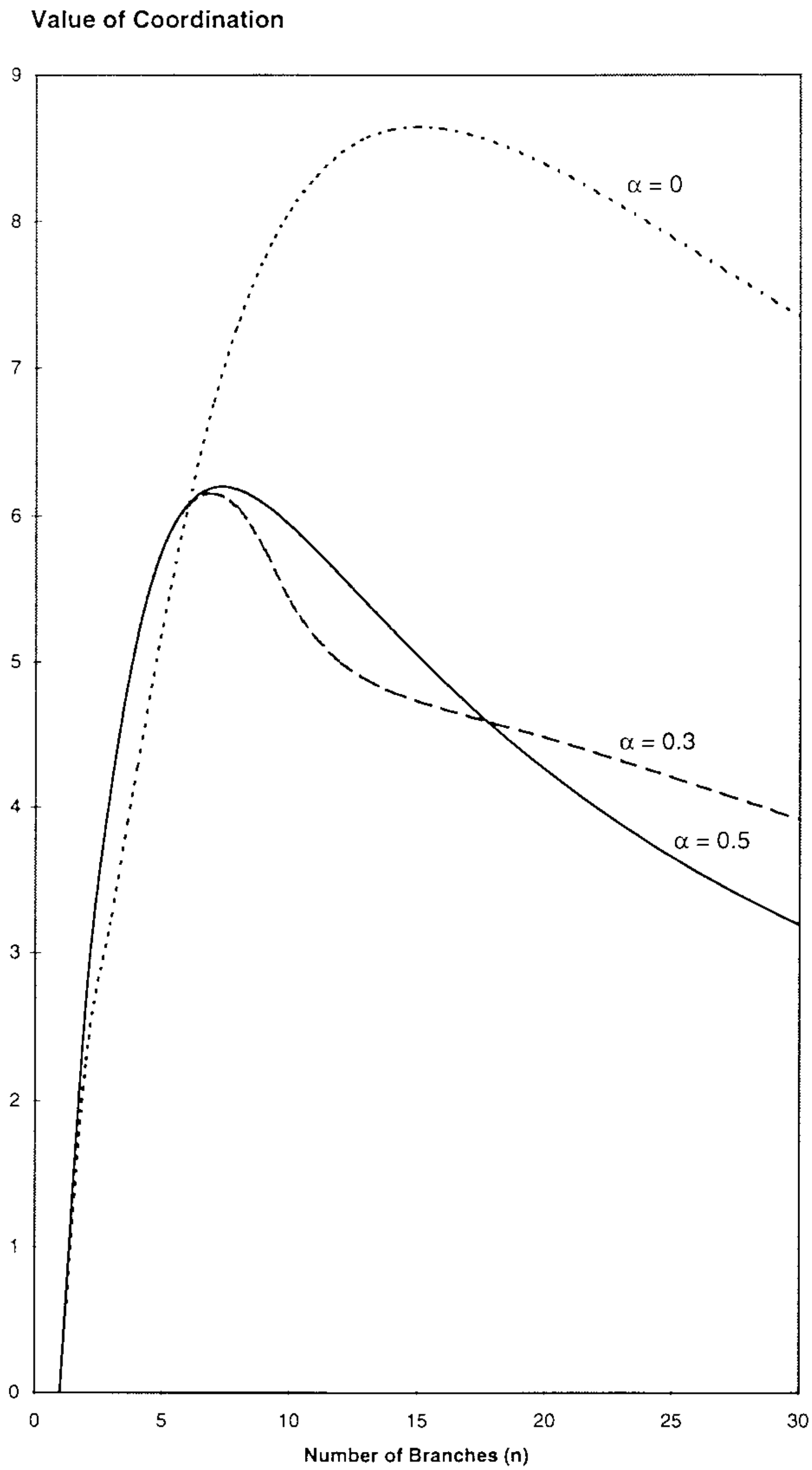

Value of Coordination
9
8
7
6
5
4
3
2
1
0
0
5
10
15
20
25
30
Number of Branches (n)
α = 0
α = 0.3
α = 0.5

Figure 4

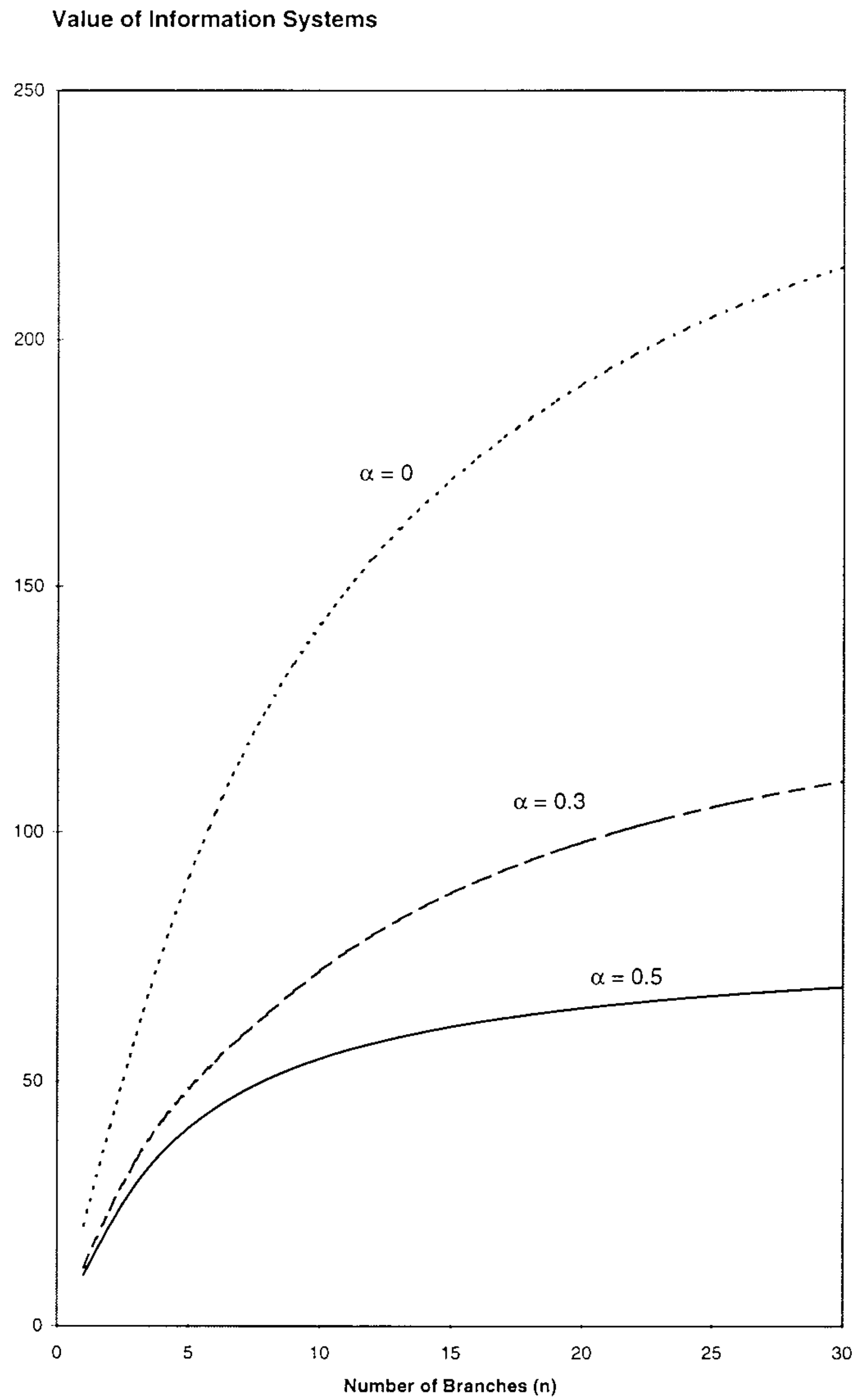

Value of Information Systems
250
200
150
100
50
0
0
5
10
15
20
25
30
Number of Branches (n)
α = 0
α = 0.3
α = 0.5

Figure 5