Buyer's Efficient E-Sourcing Structure: Centralize or Decentralize?

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ABSTRACT: Strategic sourcing, defined as a firm's key business process to identify, evaluate, configure, and negotiate purchases in important spend categories while

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managing long-term supplier relationships, is playing a significant role in sourcing strategies. The adoption of e-sourcing, defined as the use of business software (for example, using application service providers to conduct online procurement auctions) to automate or augment the aforementioned key business process, has been growing rapidly in recent years. One often-cited benefit of e-sourcing is the predicted savings, which is appealing, given the increasing pressure on cost competitiveness faced by firms. Using queuing techniques, this paper develops an economic model that captures fundamental trade-offs in a firm's e-sourcing business process as characterized by communication complexity, frequency of use, and cost of delay. This allows comparisons of two widely adopted structures for e-sourcing: the centralized structure versus the decentralized structure. Conditions under which the centralized structure is favored over the decentralized structure and vice versa are identified and illustrated with numerical examples and case evidence. These findings are robust in other settings. The paper concludes with a discussion of managerial implications.

KEY WORDS AND PHRASES: communication complexity, economic analysis, e-sourcing, organization structure, procurement, queuing, reverse auction.

THERE IS A GROWING TREND IN RECENT YEARS toward adopting e-sourcing,[1] driven primarily by more competitive and dynamic market environments, technology innovation, and supply-chain globalization. Specific driving factors include the competitive cost pressure, the business practice of global sourcing, reduction in telecommunication cost, integrated enterprise resource planning (ERP) systems, and a market shift toward the buyers [3]. Firms have reported major benefits of e-sourcing such as reduction of price paid as well as reduction of process error.[2] Firms use e-sourcing to purchase manufacturing inputs, such as semiconductors, as well as maintenance, repair, and operating (MRO) inputs, such as legal services [29] or janitorial services, with online purchasing of direct materials having caught up with and passed MRO materials [19, 20, 21, 22, 33].

We define *e-sourcing* as the use of business software (for example, using application service providers to conduct online procurement auctions) to automate or augment a firm's strategic sourcing—the key business process to identify, evaluate, configure, and negotiate purchases in important spend categories while managing long-term supplier relationships.[3]

Information technology (IT) is fundamental to e-sourcing. First, the Internet enables and enhances global sourcing practice, which is driven by pressure for purchasing savings exerted on purchasing managers by top executives. The Internet allows prequalified suppliers from around the world to bid for a firm's sourcing needs. Second, the prevalence of ERP implementations provides operational data to feed the e-sourcing platform. Third, the availability and affordability of on-demand computing, or third-party application services, makes e-sourcing cost-effective and easy [19, 20, 21, 22].

In terms of IT infrastructure, the adoption of e-sourcing requires three key components: the network/server, software, and design/redesign of the firm's business process. Business process design/redesign is the key factor for successful e-sourcing adoption, as firms often outsource the hosting and conduct of reverse auctions to a third-party application service provider (ASP), thus eliminating the need for some hardware and software investments and related implementation and maintenance costs. One of the most significant changes triggered by e-sourcing adoption is the change of procurement from a negotiation-centered to a preparation-centered process. The time and effort expended in a successful e-sourcing event are 75 percent preparation, 5 percent execution, and 20 percent fulfillment [3]. Since e-sourcing units are in charge of preparing all RFXs, such as requests for information/proposals/quotes (RFI/RFP/RFQ), and auction events, these units are becoming the bottlenecks and may be congested during peak seasons. Therefore, the fundamental problem of how to structure e-sourcing has motivated the two research questions of this paper: First, given an e-sourcing organization structure (centralized or decentralized), what should be a firm's choice of optimal IT service needs when contracting with an outside ASP? Second, in choosing the organization structure, should the firm centralize or decentralize its e-sourcing structure, and under what conditions?

Our investigation employs a unique research methodology that combines analytical modeling, in-depth interviews, and case studies. We first reviewed industry and consulting reports/surveys on e-sourcing [3, 20, 21, 33]. Then, we conducted site visits and in-depth face-to-face interviews with a small sample of leading e-sourcing adopters and their ASPs. We also participated in a major industry e-sourcing conference. Based on an analysis of information from such primary and secondary sources, as well as a survey conducted by a third party, we arrived at three critical success factors for e-sourcing: communication complexity (defined later), frequency of use, and cost of delay. While previous research has addressed these factors separately and in different contexts [1, 5, 10], this paper develops an economic model that integrates them in the unique setting of e-sourcing. The model allows us to address the aforementioned two research questions.

Literature Review

MOTIVATED BY THE BUSINESS PRACTICE of the e-sourcing process, our research is a first step toward the integration of three separate, but related, research streams: procurement auctions, business-to-business (B2B) exchanges and supply chains, and organization information processing. We now briefly review each.[4]

The first stream focuses on design, evaluation, and computation of procurement auctions. From the perspective of mechanism design, Chen et al. [8] consider efficient auctions for supply-chain procurement. Snir [38] studies multi-attribute online descending-price auctions in the presence of two contract-awarding rules (the complete information auction versus the total cost evaluation auction). Motivated by proxy bidding, Gallien and Wein [13] design a "smart market" for industry procurement with both online and offline (postauction) performance guarantees in the presence of supplier bidding capacity constraints. Using a computational approach, Parkes and Kalagnanam [34] study iterative multi-attribute as well as combinatorial procurement auctions. Chen et al. [7] model multi-attribute combinatorial procurement reverse auctions run by public entities and governments. See Pinker et al. [36] for an extensive survey of current business and research issues of online auctions.

The second stream focuses on B2B exchanges and supply chains. From the buyer's perspective, Peleg et al. [35] compare short-term e-procurement strategies versus long-term contracts, and identify conditions under which a particular strategy (pure e-procurement, pure long-term contract, or a mix of both) is optimal. Tunca and Zenios [40] investigate supply auctions and relational contracts for procurement. From the supplier's perspective, Campbell et al. [6] model search and collusion in electronic markets, and Granot and Sošić [17] investigate the responsiveness of suppliers to Internet-based exchanges by forming alliances. Wu and Kleindorfer [43] present a framework that integrates contract-spot sourcing via real options. For surveys of this line of work, see Grey et al. [18] and Kleindorfer and Wu [25].

The third stream focuses on the role of information in organization design as well as in electronic marketplaces. Galbraith [12] presents the information processing view of organization design. His view—that an organization is designed to process information efficiently—has been refined by many others. Radner [37] considers organization of decentralized information processing, revisited by Vayanos [41] in the presence of interactions. Bolton and Dewatripont [5] model the firm as a communication network, neglecting frequency of use and other domain-specific factors that we consider. They show that centralized structure is efficient. Harris and Raviv [23] identify conditions when the decentralized structure, the centralized structure, or a mix of both can be efficient. Gal-Or et al. [14] study best practices for online procurement intermediates. They show that it is desirable for the buyer to reveal the winner determination information (a supplier's overall score of its multi-item multi-attribute bids) to the suppliers in simultaneous reverse auctions, but to conceal such information if sourcing occurs via one-on-one sequential negotiation. From the perspective of information quality, Mendelson and Tunca [30, 31] study the impact to industry structures on the formation of B2B exchanges. They characterize the fundamental difference between B2B liquidity and liquidity in financial exchanges. Tunca [39] studies the relationship between private information and performance in oligopolistic procurement markets. Zhu [45] examines the role of information rules in B2B markets, demonstrating their impact on industry structure.

This paper contributes to the above literature in a number of ways. First, it considers the entire e-sourcing business process, not merely the auction. This process includes not only the procurement auction but also activities before the auction (e.g., purchasing process preparation) and after the auction (e.g., contract execution), which has been missing in the literature, but is crucial to e-sourcing business practice. Second, Bolton and Dewatripont [5] show that centralized structure is efficient, but they neglect frequency of use and other domain-specific factors that we model. In contrast, we show that decentralized structure can be efficient, depending on the trade-off among three key factors that we identify and model. Our findings are consistent with other recent theoretical findings in different contexts [23, 37, 41]. Third, our results are consistent with best business practices where decentralized e-sourcing structures are frequently observed [20]. Finally, in terms of methodology, we employ a queuing approach, which is different from that of Bolton and Dewatripont [5], but similar to other models of organization hierarchies [4]. We first use the specific case of the M/M/1 queue in deriving analytical results. Using simulation, we then consider other cases that allow exponential and bursty arrivals of purchasing requests as well as spillover. Spillovers are those purchasing requests that are routed to an e-sourcing unit that is not prespecified in processing their type. Spillover may happen in the decentralized setting when purchasing request types are temporarily unbalanced. The structural results derived from our analytical modeling seem to be robust to these extensions, and consistent with most recent theoretical findings that consider more general cost delay functions [1].

Model Presentation

ASSUME THAT A FIRM BUYS ITS INPUT VIA E-SOURCING (i.e., procurement via online reverse auctions with prequalified suppliers) during one period.[5] In designing the organization structure for e-sourcing,[6] the firm can choose either a centralized, flat structure (as illustrated in Figure 1); or a decentralized, hierarchical structure (as illustrated in Figure 2); or a hybrid, matrix structure. In this paper, we consider the choice between the two widely adopted structures, centralized versus decentralized, but not the mix of both (which is less frequently used in practice).

Given the organization structure (decentralized or centralized), the firm maximizes its total surplus from the e-sourcing practice via the choice of its ASP service capacity needs C, with a unit capacity cost of k.[7] k can be the fixed flat-rate service subscription fee the firm pays to a third-party ASP. In practice, these are multiyear long-term IT service contracts for large and medium-sized firms, short-term annual contracts, or event-based pricing for small firms.[8] We identify three critical success factors for e-sourcing: communication complexity, frequency of use, and cost of delay. We now formalize and justify each of these.

The first factor, the *communication complexity,* Γ, is the total communication cost and effort needed for a firm's purchasing request to travel through the entire e-sourcing business process. An example of such a business process is the following: a purchasing request is initiated by a firm's manufacturing division as triggered by demand forecasting or by service needs; then it enters a planning phase, which includes opportunity analysis and supplier selection; it finally reaches the execution phase, which includes auction setup, the auction itself, and contract execution.[9] Communication complexity covers this entire e-sourcing business process, including the time and effort needed before, during, and after the auction, which is essential for e-sourcing, according to Beall et al. [3]. Such time and effort captures interactions among many units (cross-functional teams) within and beyond the firm to process a purchasing request. Further, given a communication complexity Γ, the firm incurs a quadratic

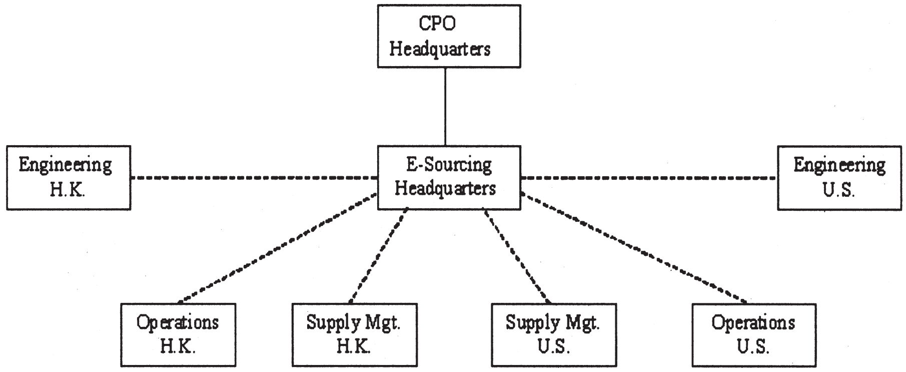


Figure 1. Example of a Centralized E-Sourcing Structure. On top of this organization structure sits the chief procurement/purchasing officer (CPO), who is responsible for satisfying the organization's entire sourcing needs.

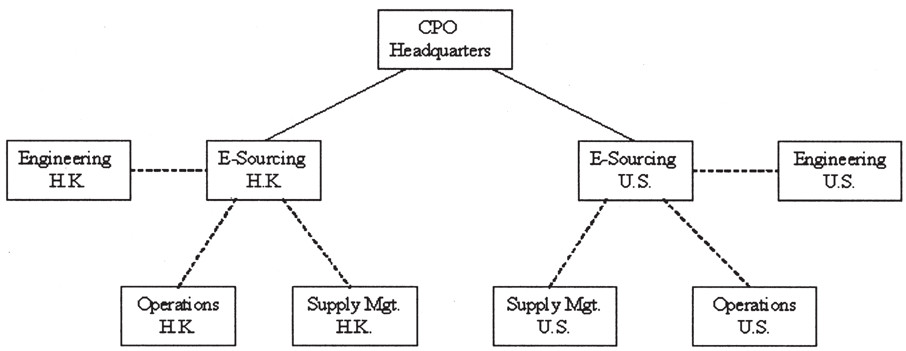


Figure 2. Example of a Decentralized E-Sourcing Structure

unit communication cost $q(\Gamma) \equiv \Gamma^2$ for e-sourcing.[10] In summary, our concept of communication complexity generalizes previous concepts of communication cost [5], which remains a special case of ours.

The second factor, *frequency of use,* is rooted in two streams of information systems (IS) research. The first argues that IS use may be the missing link in reaping business value from IT investment [10]. The second argues that learning and training are important factors in enterprise software implementation [44]. We define frequency of use as a random purchasing request. The requests are drawn from a known distribution of $\Omega(\bullet)$, with a mean arrival rate of Λ. Learning or knowledge retention is captured in $S(\Lambda) \equiv 1 - e^{-\Lambda}$, reflecting the talent of the e-sourcing unit. The function exhibits a concave learning property [44]. This is so in practice, as the e-sourcing team can learn over time and accumulate e-procurement knowledge by repeatedly using the reverse auction system, communicating with the suppliers, collaborating with the ASP, fine-tuning firm-specific dictionaries and auction templates, and so on.

The third factor, *unit cost of delay,* denoted as t, is standard in the economics of network design and Internet pricing [1]. In e-sourcing business practice, this reflects

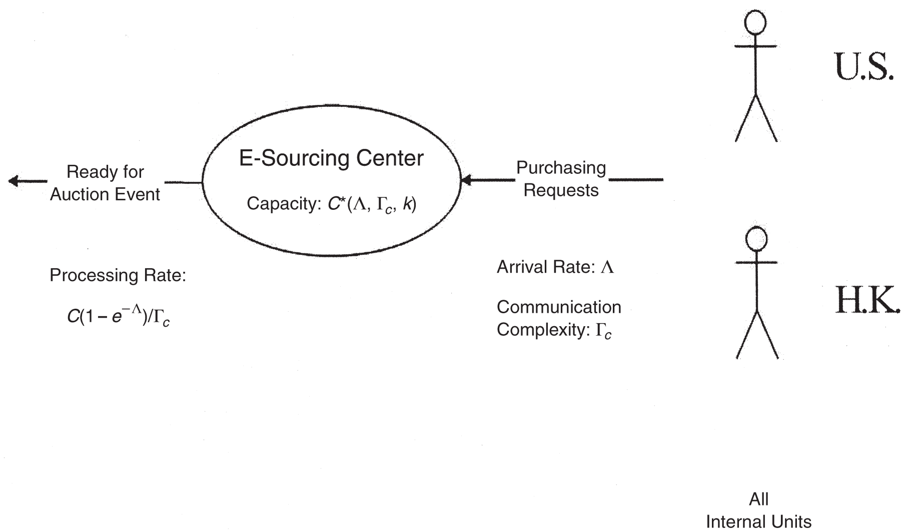


Figure 3. A Queuing Model of a Centralized E-Sourcing Structure

the right types of supply chains that a firm should be running [11, 27]. Cost of delay could be significant for firms in a dynamic environment characterized by high demand uncertainty. So e-sourcing must support these firms' needs for a responsive or agile supply chain. In contrast, cost of delay may not be significant for firms in a stable environment characterized by low demand uncertainty and low supply uncertainty [26, 27].

We model the centralized e-sourcing unit as an M/M/1 queue, with a processing rate of $C(1 - e^{-\Lambda})/\Gamma$, as depicted in Figure 3. This processing rate reflects the intuition that larger processing capacity C, or less communication complexity Γ, or more frequent use Λ, lead to an increase in processing rate, and vice versa. Denote $W(C, \Lambda, \Gamma, S(\Lambda))$ as the expected waiting time for an auction request to be processed by the e-sourcing unit.

For ease of exposition, we assume that the decentralized structure consists of only two identical servers facing the same number of auction requests drawn from the same distribution $\Omega(\bullet)$, as depicted in Figure 4. This means that the firm has the same business needs, but may structure its e-sourcing process to be either centralized or decentralized. In the decentralized case, however, we assume *economy of specialization* [5]: each e-sourcing server has accumulated specific knowledge to efficiently process specific types of requests. Internal traffic (purchasing requests) is automatically directed according to an a priori belief about the total cost of delay and communication. An auction request of a given type is self-directed to the "matching" e-sourcing server that is most efficient in processing that type of request.

Let V denote the total trade surplus for the firm over the period by using e-sourcing. Total surplus is assumed to be independent of the cost of delay t. This reflects the e-sourcing business practice that the buyers rather than the suppliers control when and how often to run auctions.

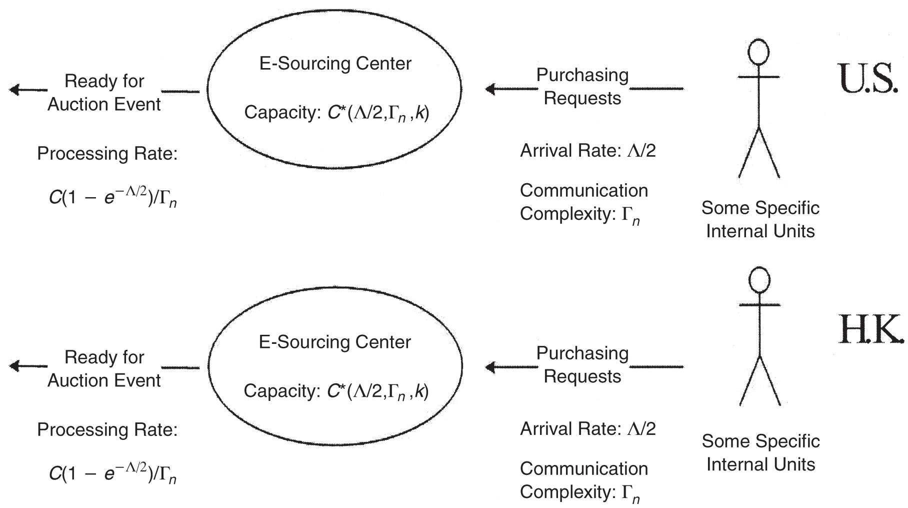


Figure 4. A Queuing Model of Decentralized E-Sourcing Structure

Results

IN THIS SECTION, WE PRESENT OUR FORMAL ANALYSES AND FINDINGS, in conjunction with the discussion of the intuition behind these theoretical results. All proofs can be found in Appendix B.

We begin with a formulation of a firm's decision problem—to choose its IT service capacity needs C to maximize its total surplus over the period. We derive the firm's optimal choice and associated expected waiting time under each structure. We identify specific conditions under which one structure is favored over the other, and vice versa, as measured by the difference of their optimal performance. The buyer's decision problem with respect to a given structure is our starting point.

Centralized Structure (c)

Under such a design, all of the firm's purchasing requests are handled by a single e-sourcing server, as illustrated in Figure 3. The firm's decision is to choose its IT service needs (capacity C) to maximize its total surplus over the period:

$$\begin{aligned}&\max_C \Lambda \int_{V>0,t>0} \left(V - W\left(C,\Lambda,\Gamma_c,S(\Lambda)\right)t\right) d\Omega(V,t) - \Lambda q\left(\Gamma_c\right) - kC \\ &\qquad = \max_C \Lambda\left(\bar{V} - W\left(C,\Lambda,\Gamma_c,S(\Lambda)\right)\bar{t} - q\left(\Gamma_c\right)\right) - kC,\end{aligned} \tag{1}$$

where $\bar{V}$ and $\bar{t}$ denote the mean of V and t, respectively.

The first term in Equation (1) is the total net benefit accrued from all auctions conducted by the firm over the period. The second term is the communication cost incurred to the firm. The third term is the firm's total IT investment (i.e., total ASP service subscription cost incurred over the period). The equality holds due to the assumption that V and t are independent. Our contrasting case is the firm's problem under the decentralized structure.

Decentralized Structure (n)

The optimal IT service capacity needs can be obtained by solving the firm's problem:

$$\max_{C} \Lambda \int_{V>0,t>0} \left(V - W\left(\frac{C}{2}, \frac{\Lambda}{2}, \Gamma_n, S\left(\frac{\Lambda}{2}\right)\right) t \right) d\Omega(V,t) - \Lambda q(\Gamma_n) - kC$$
$$= \max_{C} \Lambda \left(\bar{V} - W\left(\frac{C}{2}, \frac{\Lambda}{2}, \Gamma_n, S\left(\frac{\Lambda}{2}\right)\right) \bar{t} - q(\Gamma_n) \right) - kC. \tag{2}$$

Optimal IT Service Capacity

Using standard results in queuing theory [24], since $q(\Gamma) \equiv \Gamma^2$, Equations (1) and (2) can be rewritten as Equations (3) and (4), respectively:

$$\max_{C} \Lambda \left(\bar{V} - \frac{1}{C\left(1 - e^{-\Lambda}\right)/\Gamma_c - \Lambda} \bar{t} - \Gamma_c^2 \right) - kC \tag{3}$$

$$\max_{C} \Lambda \left(\bar{V} - \frac{1}{C\left(1 - e^{-\frac{\Lambda}{2}}\right)/2\Gamma_n - \Lambda/2} \bar{t} - \Gamma_n^2 \right) - kC. \tag{4}$$

Let C_c^* denote the optimal capacity for the centralized structure and C_n^* denote the optimal capacity for the decentralized structure. It is straightforward to show the concavity of the objective functions in Equations (3) and (4). The optimal solutions of Equations (3) and (4) give rise to

$$C_c^* = \frac{\Lambda \Gamma_c}{1 - e^{-\Lambda}} + \frac{\sqrt{k \Lambda \bar{t} \Gamma_c \left(1 - e^{-\Lambda}\right)}}{k\left(1 - e^{-\Lambda}\right)}$$

and

$$C_n^* = \frac{\Lambda \Gamma_n}{1 - e^{-\frac{\Lambda}{2}}} + \frac{\sqrt{2k \Lambda \bar{t} \Gamma_n \left(1 - e^{-\frac{\Lambda}{2}}\right)}}{k\left(1 - e^{-\frac{\Lambda}{2}}\right)}.$$

Note that optimal capacities are increasing in arrival rate (Λ), communication complexity (Γ), and cost of delay ($\bar{t}$), but are decreasing in unit capacity cost (k).

Expected Waiting Time

The expected waiting times are

$$W_c^* = \sqrt{\frac{k}{\Lambda \bar{t}}} \sqrt{\frac{\Gamma_c}{\left(1 - e^{-\Lambda}\right)}}$$

and

$$W_n^* = \sqrt{\frac{k}{\Lambda \bar{t}}} \sqrt{\frac{2\Gamma_n}{\left(1 - e^{-\frac{\Lambda}{2}}\right)}}.$$

Let $\Pi_c(C_c^*)$ and $\Pi_n(C_n^*)$ denote the optimal total surplus of centralized structure and decentralized structure, respectively. We have

$$\Pi_c\left(C_c^*\right) = \Lambda\left(\bar{V} - \frac{1}{C_c^*\left(1 - e^{-\Lambda}\right)/\Gamma_c - \Lambda}\bar{t} - \Gamma_c^2\right) - kC_c^*$$

and

$$\Pi_n\left(C_n^*\right) = \Lambda\left(\bar{V} - \frac{1}{C_n^*\left(1 - e^{-\frac{\Lambda}{2}}\right)/2\Gamma_n - \Lambda/2}\bar{t} - \Gamma_n^2\right) - kC_n^*.$$

We now investigate the effect of three factors—communications complexity, frequency of use, and cost of delay—on a firm's choice of its e-sourcing structure.

Intuitively, when communication complexity is very high, a firm should decentralize its decision rights to take advantage of local or specialized knowledge of a specific e-sourcing agent, suggesting the adoption of a decentralized structure. When frequency of use is low, it is difficult to realize economy of specialization benefits, which favors a centralized structure. When cost of delay is high, centralized structure becomes appealing. It enables pooling of e-sourcing requests, thus effectively reducing expected waiting time. Finally, when communication complexity is very low, a firm should centralize its decision making to benefit from full information communication and sharing. We show the correctness of these intuitive arguments and determine the associated conditions by measuring the performance difference $\Pi_c(C_c^*) - \Pi_n(C_n^*)$ between the centralized and decentralized structures. Our model shows that, while communication complexity plays a pivotal role in determining a firm's choice of structure, under certain conditions when communication complexity is low or medium high, other factors such as frequency of use and cost of delay become critical.

We investigate the effect of communication complexity by comparing Γ_c to Γ_n in four possible cases: (1) $\Gamma_c \geq 4\Gamma_n$; (2) $2\Gamma_n \leq \Gamma_c < 4\Gamma_n$; (3) $\Gamma_n \leq \Gamma_c < 2\Gamma_n$; and (4) $\Gamma_c < \Gamma_n$. We state our main results in four propositions, each corresponding to one case.

> *Proposition 1 (Case of Very High Communication Complexity): Assuming that $\Gamma_c \geq 4\Gamma_n$, then the decentralized structure dominates the centralized structure, regardless of frequency of use or cost of delay.*

Denote Λ_1 as the root of

$$\sqrt{\frac{\left(1-e^{-\Lambda}\right)}{\left(1-e^{-\frac{\Lambda}{2}}\right)}}\sqrt{2\Gamma_n}-\sqrt{\Gamma_c}=0.$$

> *Proposition 2 (Case of Medium High Communication Complexity): Assuming that $2\Gamma_n \leq \Gamma_c < 4\Gamma_n$, then the following is true: (a) if frequency of use is high in that it exceeds a threshold, $\Lambda \geq \Lambda_1$, then decentralized structure is preferred; (b) however, if $\Lambda < \Lambda_1$, then decentralized structure is preferred if $\bar{\tau}$ is capped by a threshold $\bar{\tau} < \theta(\Lambda, \Gamma_n, \Gamma_c)$; otherwise, if $\bar{\tau} \geq \theta(\Lambda, \Gamma_n, \Gamma_c)$, then centralized structure is preferred.*

As expected, frequency of use comes into play when learning in a specialized e-sourcing network is beneficial. A sufficient amount of e-sourcing requests (exceeding a lower bound Λ_1) ensures that each e-sourcing event sustains a certain level of specialization via learning. What happens if the heavy-traffic condition is violated? In this case, when the number of purchasing requests is low, cost of delay emerges as a significant influence for whether centralized structure dominates the decentralized structure.

Next, we denote Λ_2 as the smallest root of

$$\Lambda\left(\Gamma_n^2-\Gamma_c^2\right)+k\frac{\Lambda}{1-e^{-\Lambda}}\left(\frac{1-e^{-\Lambda}}{1-e^{-\frac{\Lambda}{2}}}\Gamma_n-\Gamma_c\right)=0.$$

> *Proposition 3 (Case of Low Communication Complexity): Assuming that $\Gamma_n \leq \Gamma_c < 2\Gamma_n$, then the following is true: (a) if $\Lambda \geq \Lambda_2$, then decentralized structure is preferred if $\bar{\tau} < \theta(\Lambda, \Gamma_n, \Gamma_c)$; otherwise, if $\bar{\tau} \geq \theta(\Lambda, \Gamma_n, \Gamma_c)$, then centralized structure is preferred; (b) however, if $\Lambda < \Lambda_2$, then centralized structure is preferred.*

Proposition 3 shows that when the gap between centralized and decentralized communication complexity further shrinks, frequency of use and cost of delay play more important roles, pushing out the boundary for adoption of centralized structure. Our final proposition shows that if such communication complexity reverses, then centralized structure dominates.

Proposition 4 (Case of Very Low Communication Complexity): Assuming that $\Gamma_c < \Gamma_n$, *then the centralized structure dominates the decentralized structure, regardless of frequency of use or cost of delay.*

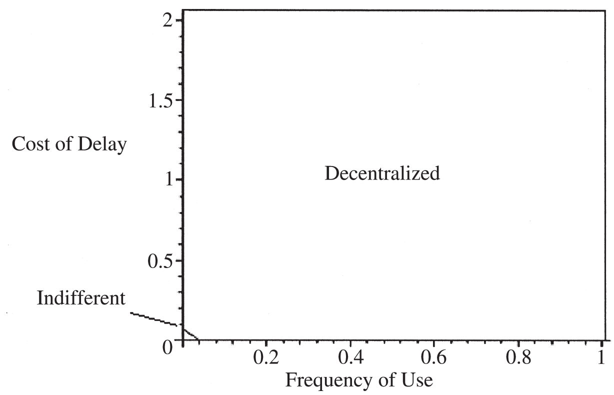
Numerical Examples and Case Evidence

IN THIS SECTION, WE PRESENT SOME NUMERICAL EXAMPLES to illustrate managerial insights stemming from the theoretical results followed by real-world case evidence.

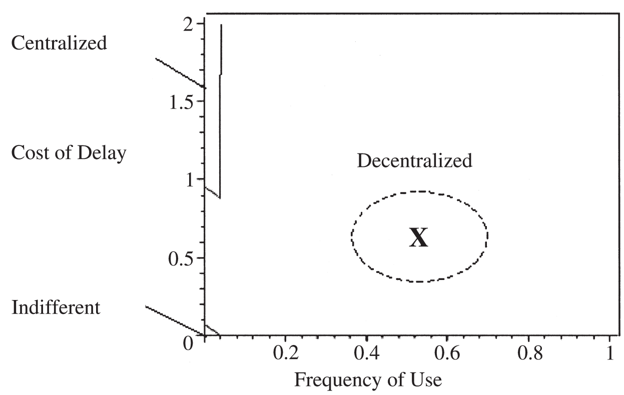
Plotted in Figure 5 are model-recommended optimal structure choices parameterized by frequency of use Λ (the horizontal x-axes) and cost of delay t (the vertical y-axes). First, Figure 5a illustrates the case in which a decentralized structure is always favored due to savings resulting from communication complexity (i.e., when $\Gamma_c \geq 4\Gamma_n$). Second, as the communication complexity gap decreases (i.e., when $2\Gamma_n \leq \Gamma_c < 4\Gamma_n$), while decentralized structure still dominates the choice as depicted in Figure 5b, there are scenarios, such as the upper left corner of Figure 5b, where a centralized structure replaces a decentralized one. This result is conditioned on the frequency of use Λ being very small or the cost of delay t being very large. Finally, Figure 5c shows that the communication complexity gap decreases further (i.e., when $\Gamma_n \leq \Gamma_c < 2\Gamma_n$), so a centralized structure dominates the structure choice. This is conditioned on low frequency of use or high cost of delay. Otherwise, a decentralized structure is more appropriate. There are also rare situations where either frequency of use or cost of delay is extremely low. In this case, the firm should be indifferent between choosing centralized or decentralized structure. (See the bottom-left corner of Figure 5.)

We illustrate our findings with three published e-sourcing cases, some updated with interviews by the study team.

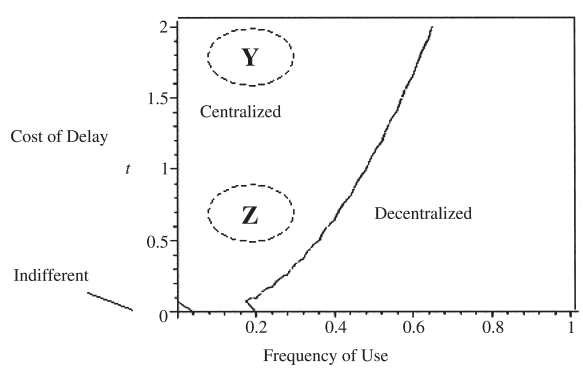
Case 1. Company X is a \$7.5 billion global manufacturer of a portfolio of branded consumer products. Company X is a market-driven company, and its business environment is characterized by the need to focus on product innovation, product development, and time to market. This puts pressure on their sourcing community, which is composed of 26 divisions that form four groups, each led by a purchasing director. E-sourcing is viewed as a key tool to meet the cost target of the enterprise, which is set to reduce total cost by 5 percent year after year [32]. Company X's e-sourcing business practice fits into Figure 5b. With such a diverse product mix and not much commonality in raw materials sourcing, decentralized sourcing would match their business needs best. The key driver of their e-sourcing structure is the relatively large difference between centralized and decentralized communication complexity. In addition, market dynamics (leading to a high cost of delay as previous discussed) and frequency of use also favor a decentralized structure.



Case (a): $\Gamma_n = 1$, $\Gamma_c = 4.1$. Decentralized structure dominates when centralized communication complexity is high.



Case (b): $\Gamma_n = 1$, $\Gamma_c = 2.1$. When frequency of use is low and cost of delay is high, centralized structure dominates.



Case (c): $\Gamma_n = 1$, $\Gamma_c = 1.1$. Centralized structure is more appropriate as its communication complexity decreases.

Figure 5. Numerical Examples Illustrating Propositions and Case Evidence: (a) $\Gamma_c \geq 4\Gamma_n$; (b) $2\Gamma_n \leq \Gamma_c < 4\Gamma_n$; (c) $\Gamma_n \leq \Gamma_c < 2\Gamma_n$. Other parameterization $V = 100$, $k = 1$.

Case 2. Company Y is a leading equipment maker for home transmission networks and subscriber systems. Sourcing is critical for Company Y, as the company spent over $1 billion dollars in global purchasing (mostly from Asia) out of revenue under $2 billion dollars in 2003. Company Y's business is characterized by demand and supplier uncertainty, causing a high cost of delay. For a specific commodity product, Company Y conducts only an annual auction, indicating a low frequency of use. Company Y invested heavily within the company and with its suppliers to reduce communication complexity. Company Y develops companywide standards and trains internal employees, as well as its suppliers. Company Y does not "experiment on their suppliers"; rather, it focuses on supplier acceptance by sharing as much information as suppliers need to make an accurate bid, by "giving the suppliers some rules before the event so they can well understand the drawings and ask questions before the event occurs," and being consistent so that "suppliers do not get caught off guard" [22].[11] The e-sourcing structure of Company Y fits into the upper-left corner of Figure 5c. The company has been reducing communication complexity. This, in conjunction with business needs for an agile supply chain, warrants a centralized e-sourcing structure. This is exactly what happened at Company Y, which migrated from a previous decentralized sourcing structure to the current centralized e-sourcing structure.

Case 3. Company Z is a leading financial service firm. The company's sourcing process has evolved from the "old school" of decentralized business partner collaboration to the "new school" of centralized collaboration in a virtual environment. While its previous sourcing process is inconsistent and labor-intensive, the new business practice is to utilize a standard digital e-sourcing process. Previous paper-driven RFI/RFP responses have given way to paperless responses with online reviews. Also, the lengthy negotiation process (in weeks) has been replaced by competitive bidding (in hours). The current successful methods of supplier sourcing for commodities such as group meetings and events, facilities (landscaping, window washing), and personnel programs have led to consideration of future roll outs for other MRO goods, such as telecommunications, print services, and retail fixtures. The e-sourcing structure of Company Y fits into the bottom-left corner of Figure 5c. The company has been reducing communication complexity by following its Six Sigma DMAIC (define-measure-analyze-improve-control) process, by creating a specific template for sourcing supplier commodities, by working closely with sourcing specialists who handle supplier contracts, and by learning to document results and savings. This, in conjunction with its business environment (where its core is financial services) and business needs (sourcing mainly MRO goods, characterized by low cost of delay and low frequency of use), calls for a centralized e-sourcing structure [42].

Extensions

IN THIS SECTION, USING SIMULATIONS, we extend our model to treat other settings, demonstrating robustness of the findings in this paper. We first show the robustness of our results to exponential arrivals as well as shocks or spikes in purchasing requests.

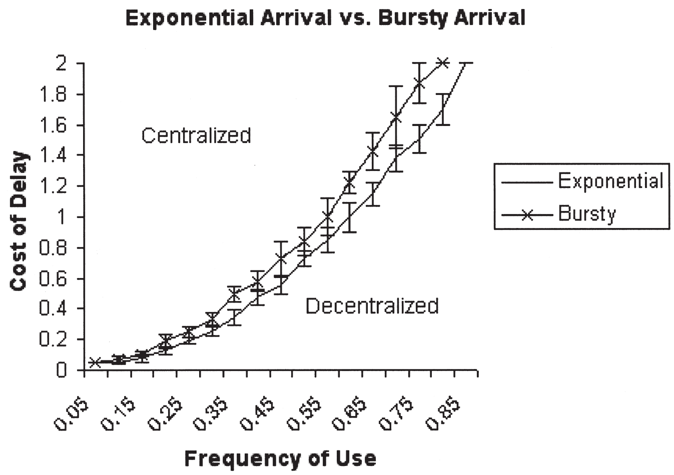


Figure 6. Robustness of Structural Results: Exponential Arrival and Shocks. Other parameterization $V = 100$, $k = 1$, $\Gamma_n = 1$, $\Gamma_c = 1.1$.

The shocks, in practice, may reflect the seasonal demand for a firm's products. We then show the robustness of our results to spillover.

Robustness of Structural Results: Exponential Arrival and Shocks

Our first extension is to analyze cases when the arrival process of purchasing requests is exponential and bursty (shocks or spikes). This fits some scenarios, such as seasonality, better than simple Poisson arrivals, as assumed in our previous M/M/1 modeling. We use the standard nonhomogeneous (nonstationary) Poisson to represent bursty arrivals. In the bursty process, there are two levels of arrival intensities, H and L, where we assume $H = 2L$. H and L represent in-season and off-season workload. The arrival rate changes between these two levels periodically. Figure 6 depicts the optimal structural decisions with exponential and bursty arrivals. We find that spikes in the arrival process do not qualitatively change our analytical results. However, a decentralized structure becomes more favorable than a centralized one, especially when the frequency of use is high. This is not surprising; decentralized structure can better "absorb" shocks by splitting them into smaller ones. In contrast, centralized structure is unable to do so.

Robustness of Structural Results: Spillover

Our second extension is to allow spillover in the decentralized structure. Spillover means that a type A request will not always be routed to the specific e-sourcing unit dedicated to processing type A requests. It may be routed to the other e-sourcing unit dedicated to processing type B requests. The actual routing depends on the congestion

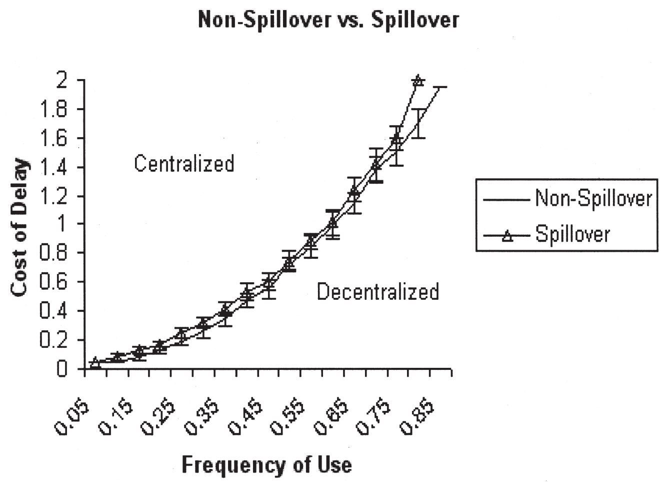


Figure 7. Robustness of Structural Results: Spillover. Other parameterization $V = 100$, $k = 1$, $\Gamma_n = 1$, $\Gamma_c = 1.1$.

level of both e-sourcing units. Spillover has been used in e-sourcing practice [19]. The basic rationale of spillover is to reduce waiting time, which is equivalent to reduced cost of delay, raising the threshold value $\theta(\Lambda, \Gamma_n, \Gamma_c)$. This is achieved by balancing arrivals and utilizing server capacity more efficiently. But this additional benefit trades off with additional cost incurred due to the mismatch of requests and the server. If such additional benefit exceeds additional cost (due to mismatching), spillover would enlarge the decentralized region in Figure 5c by pushing the curve toward the northwest direction. This intuition is confirmed by our simulation as depicted in Figure 7. We find that real-time control of spillover increases adoption of decentralized structure, when the traffic is heavy (i.e., frequency of use is high). In any case, the structure of our previous analytical results seems to be robust.

Conclusion and Discussions

MOTIVATED BY THE BUSINESS PRACTICE OF E-SOURCING, this paper develops an economic model that captures key components in choosing a firm's e-sourcing structure: communication complexity, frequency of use, and cost of delay. Our main contribution is to building new theory. We identified the conditions under which centralized and decentralized structures for e-sourcing are optimal. Our results also have practical implications.

Managerial Implications

The implications for our findings to managers are threefold. First, as summarized in Table 1, our model supports e-sourcing structure choice by allowing managers to

Table 1. Summary of Findings

Communication complexity	Frequency of use	Cost of delay	Choice	Comments
Very high ($\Gamma_c \geq 4\Gamma_n$)			Decentralized	Case (1) Proposition 1 Figure 5a
Medium high ($2\Gamma_n \leq \Gamma_c < 4\Gamma_n$)	High ($\Lambda \geq \Lambda_1$)		Decentralized	Case (2) Proposition 2 Figure 5b
	Low ($\Lambda < \Lambda_1$)	High ($\bar{t} \geq \theta(\Lambda, \Gamma_n, \Gamma_c)$)	Centralized	
		Low ($\bar{t} < \theta(\Lambda, \Gamma_n, \Gamma_c)$)	Decentralized	
Low ($\Gamma_n \leq \Gamma_c < 2\Gamma_n$)	High ($\Lambda \geq \Lambda_2$)	High ($\bar{t} \geq \theta(\Lambda, \Gamma_n, \Gamma_c)$)	Centralized	Case (3) Proposition 3 Figure 5c
		Low ($\bar{t} < \theta(\Lambda, \Gamma_n, \Gamma_c)$)	Decentralized	
	Low ($\Lambda < \Lambda_2$)		Centralized	
Very low ($\Gamma_c < \Gamma_n$)			Centralized	Case (4) Proposition 4

trade off critical success factors explicitly. Our interactions with industry executives find that the savings resulting from such strategic structural changes are not only substantial but also sustainable.[12] Second, given an e-sourcing structure, our model provides managers with actionable guidance for their firms' optimal ASP IT service capacity needs for e-sourcing. Finally, our model has implications for learning and training. Firms can elevate their e-sourcing knowledge (as captured in $S(\Lambda)$) and add value by training (i.e., by increasing Λ artificially). This can be achieved, for example, by training globally both the buyers and their suppliers, by training the trainers, by helping the buyers network with suppliers and other buyers, and by running mock auctions for the suppliers. The rationale is that in e-sourcing, "Once a skill is obtained, it is retained."[13]

Limitations

Our model has limitations. First, it focuses on e-sourcing, but does not consider "total" sourcing activities, such as traditional face-to-face negotiation, which may be heavily based on relationships. Further, we may have left out important factors for e-sourcing such as the ease of monitoring and control for top management. Second, to empirically test our findings, we need a creative way to operationalize and to measure a firm's communication complexity. Finally, we do not model interfirm processes where the e-sourcing structure of the suppliers may also play a role. These are future research opportunities.

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Notes

1. AMR research predicted that the market for e-sourcing will grow to approximately $1.8 billion by 2006 from $350 million in 2001 (see note 3 and [33]).

2. Aberdeen Group predicted that businesses could save $1.7 trillion annually by employing e-sourcing tactics (see note 3). A study sponsored by the Center for Advanced Purchasing Studies (CAPS) reported a 15 percent average reduction on price paid, and a 30 percent to 90 percent reduction on process errors [3].

3. Speech delivered by M.F. Morel at the IMPACT lecture series, College of Management, Georgia Institute of Technology, Atlanta, 2005.

4. For an extensive and excellent body of knowledge, the reader is referred to articles in the following special issues: the special section of *Electronic Markets* on "B2B Reassessment" [9];

the special issue of *Management Science* on "Electronic Business" (two volumes [15, 16]); and the special issue of *Management Science* on "Electronic Markets" [2].

5. Note that the firm may well use other means, such as face-to-face negotiations, for its sourcing needs.

6. Typically, firms form cross-functional teams for each purchasing request, including the e-sourcing unit, engineers, supply management, operations, and so on.

7. We summarize our notation in Appendix A.

8. According to a major application service provider, a large (medium, small) firm is defined as "Global 200 (2000, 1 million)" with revenues over $10 billion ($1 billion, $20 million) (see note 3).

9. The example is a real-life Six Sigma DMAIC e-sourcing process that has been used by a leading financial service firm [42].

10. Note that this is a special case of the more general convex cost assumption, which is standard in the economics literature on information processing [5, 37]. In our e-sourcing context, this can be thought of as the cost of distributing internal communication packages, identifying potential suppliers, finalizing RFQs, and making short lists of suppliers to be invited, drafting terms and conditions, and sending out supplier registration letters. Not all these efforts are easily codifiable in any reusable templates [28].

11. Private communication with Scientific–Atlanta executive R.H. DeHart, 2004.

12. Private communications with Procuri executive J. Madrid, February 2005.

13. Private communication with Deposco executive C. Clark, 2004.

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Appendix A. Summary of Notation

Λ: Average arrival rate of internal requests for auctions.

Γ: Communication complexity between e-sourcing unit and other units in a firm, specifically in the forms of Γ_c, Γ_n as the following.

Γ_c: Communication complexity for centralized structure.

Γ_n: Communication complexity for decentralized structure.

$S(\Lambda)$: Knowledge level of the e-sourcing group.

C: Total capacity of e-sourcing group.

$W(\bullet)$: Expected waiting time for an auction request to be processed.

t: Rate of the cost of delay for an auction request (cost per unit of time).

V: Trade surplus of an auction for the firm.

$q(\Gamma)$: Internal communication cost incurred on other units.

$\Omega(V, t)$: Cumulative joint distribution.

k: Unit capacity cost.

Appendix B. Proofs

Derivations of Optimal Capacity

THE FIRST-ORDER CONDITIONS with respect to C for Equations (3) and (4) result in

$$-\Lambda\bar{t}\,\frac{\left(1-e^{-\Lambda}\right)/\Gamma_c}{\left[C\left(1-e^{-\Lambda}\right)/\Gamma_c-\Lambda\right]^2}+k=0$$

and

$$-\Lambda\bar{t}\,\frac{\left(1-e^{-\frac{\Lambda}{2}}\right)/2\Gamma_n}{\left[C\left(1-e^{-\frac{\Lambda}{2}}\right)/2\Gamma_n-\Lambda/2\right]^2}+k=0.$$

The respective solutions to these equations are

$$C_{1,2}=\frac{\Lambda\Gamma_c}{1-e^{-\Lambda}}\pm\frac{\sqrt{k\Lambda\bar{t}\,\Gamma_c\left(1-e^{-\Lambda}\right)}}{k\left(1-e^{-\Lambda}\right)}$$

and

$$C_{1,2} = \frac{\Lambda\Gamma_n}{1-e^{-\frac{\Lambda}{2}}} \pm \frac{\sqrt{2k\Lambda\bar{t}\Gamma_n\left(1-e^{-\frac{\Lambda}{2}}\right)}}{k\left(1-e^{-\frac{\Lambda}{2}}\right)}.$$

Checking the second-order conditions of Equations (3) and (4) at these points results in the optimal solutions. Q.E.D.

Proof of Proposition 1

$$\begin{aligned}
&\Pi_c\left(C_c^*\right)-\Pi_n\left(C_n^*\right)\\
&=\Lambda\left(\Gamma_n^2-\Gamma_c^2\right)+k\Lambda\left(\frac{\Gamma_n}{1-e^{-\frac{\Lambda}{2}}}-\frac{\Gamma_c}{1-e^{-\Lambda}}\right)\\
&+2\sqrt{k\Lambda\bar{t}}\left(\sqrt{\frac{2\Gamma_n}{\left(1-e^{-\frac{\Lambda}{2}}\right)}}-\sqrt{\frac{\Gamma_c}{\left(1-e^{-\Lambda}\right)}}\right)\\
&=\Lambda\left(\Gamma_n^2-\Gamma_c^2\right)+k\frac{\Lambda}{1-e^{-\Lambda}}\left(\frac{1-e^{-\Lambda}}{1-e^{-\frac{\Lambda}{2}}}\Gamma_n-\Gamma_c\right)\\
&+2\sqrt{\frac{k\Lambda\bar{t}}{\left(1-e^{-\Lambda}\right)}}\left(\sqrt{\frac{\left(1-e^{-\Lambda}\right)}{\left(1-e^{-\frac{\Lambda}{2}}\right)}}\sqrt{2\Gamma_n}-\sqrt{\Gamma_c}\right).
\end{aligned} \tag{B1}$$

It is straightforward to show that $\Lambda/(1 - e^{-\Lambda})$ is strictly increasing and $(1 - e^{-\Lambda})/(1 - e^{-\Lambda/2})$ is strictly decreasing in Λ. Applying L'Hopital's rule, we have

$$\lim_{\Lambda\to 0}\frac{\Lambda}{1-e^{-\Lambda}}=1,\quad \lim_{\Lambda\to 0}\frac{1-e^{-\Lambda}}{1-e^{-\frac{\Lambda}{2}}}=2.$$

Therefore,

$$\lim_{\Lambda \to 0} \Pi_c\left(C_c^*\right) - \Pi_n\left(C_n^*\right) = k\left(2\Gamma_n - \Gamma_c\right) + 2\sqrt{k\bar{t}}\left(\sqrt{4\Gamma_n} - \sqrt{\Gamma_c}\right). \tag{B2}$$

If $\Gamma_c \geq 4\Gamma_n$, then all three terms in Equation (B1) will be negative. Q.E.D.

Proof of Proposition 2

Since $2\Gamma_n \leq \Gamma_c < 4\Gamma_n$ and $((1 - e^{-\Lambda})/(1 - e^{-\Lambda/2})) < 2$, the first two terms in Equation (B1) are negative. Case (a) immediately follows from this, since the third term is also negative if $\Lambda \geq \Lambda_1$. Consider case (b) when $\Lambda < \Lambda_1$. Note in this case, the third term is positive and is monotonic in $\bar{t}$. Clearly, there exists a threshold value $\theta(\Lambda, \Gamma_n, \Gamma_c)$ above which the sign of Equation (B1) is positive, and below which it is negative. Q.E.D.

Proof of Proposition 3

The proof of case (a) when $\Lambda \geq \Lambda_2$ is omitted, as it is similar to the proof of case (b) in Proposition 2. Consider case (b) when $\Lambda < \Lambda_2$. The third term is positive. The sum of the first two terms is also positive, given the definition of Λ_2 and Equation (B2). Therefore, the sign of Equation (B1) is positive. Q.E.D.

Proof of Proposition 4

By assumption $\Gamma_c < \Gamma_n$, therefore all three terms in Equation (B1) are positive. This ensures that the sign of Equation (B1) is positive. Q.E.D.