

Supply Chain Broker Operations: A Network Perspective

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Abstract

Recent work in social network analysis has examined performance of various organizations from a network perspective. This paper presents a network analysis of spot-market broker operations in supply chain management, based on findings from our empirical study of a specific firm in the industry. By modeling the connections between the brokers and the vendors they contact, we define metrics that correlate the strategies for selecting the vendors with profitability, which allows for the identification of potentially good operating policies. We find that it is not just the number of connections between brokers and vendors that impact profitability, but also the quality of those connections. We develop an approach to quantify the quality of connections and demonstrate the extent to which this approach can not only predict system performance but also serve as a tool to evaluate the performance of individual brokers.

1. Introduction

Current economic trends, including significant changes in import volumes, fuel prices, and manufacturing output, have led to dramatic changes in demand for truckload freight

transportation and the capacity available to service the freight. Efficient asset management is critical for both shippers and carriers to remain competitive. In truckload transportation, efficient operations are characterized by minimum deadhead (the miles a truck must travel empty to the shipper), and high utilization of drivers and trucks. Asset utilization has far-reaching implications for supply chains. Highly efficient operations allow shippers to bring their goods to market at lower cost and carriers to maximize profits, while minimizing the cost of public externalities, such as air and noise pollution, consumption of fossil fuels, wear and tear on public roads, and accidents.

There are some 250,000 carriers in North America, ranging from giants like Schneider National and Wal*Mart's private fleet to single-owner operators. Some portion of the freight contracted to and hauled by these carriers occurs on a consistent basis, which results in patterns of empty and available trucks that can be scheduled by carriers efficiently. However, a significant portion of shipments are irregular. These are commonly referred to a spot freight or transactional (rather than contractual) freight. These loads cannot be scheduled far in advance, nor can the resulting empty trucks be considered more than a day or so in advance of their availability.

If every truck and every load were controlled by a single entity, efficient matching of trucks and loads could be derived through an optimization procedure, yielding low deadhead to cover all of the loads while using as few trucks as possible. In reality, no such entity exists; each shipper is primarily concerned with minimizing the cost of moving freight, and each carrier is primarily concerned with maximizing profits. A global optimization would additionally be complicated by the fluidity of the network in that the capacity map is constantly evolving through time. A true global optimization would have to not only optimize geographically, but also optimize inter-temporally. Given the very fragmented and generally deregulated nature of this industry, the state

of equilibrium includes a level of inefficiency, with excess deadhead and loads that do not move when shippers wish they would.

Freight brokers, or transportation intermediaries, entered the marketplace following the deregulation of the industry in the early 1980s. Freight brokers act as middlemen between shippers and carriers. New technology has continued to advance the capabilities of intermediaries, beginning with the adoption of fax machines in the 1980s¹ and continuing with web-based matching services in the late 1990s. According to Armstrong & Associates, the third party logistics industry reached revenues of \$122 billion in 2007.² The industry is highly competitive and efficient use of resources, including employees who broker loads between carriers and shippers, is critical for success.

This paper examines third-party broker operations from a firm perspective. In particular, we study the question of how to best manage resources in a constrained operating environment from the perspective of a third-party broker. We focus on spot market operations given a fixed number of loads in need of transport. The resulting problem is to optimize the activities of brokers who work with carriers to transport the load. In such fragmented industries, operations can be difficult to analyze because a large portion of the carriers are small and fairly unsophisticated, and as a result, quality information is difficult to attain or simply unavailable. Pricing data, as an example, is often never recorded in any form during the process of negotiation. This research would not be possible without the collaboration of a technology forward partner of sufficient scale willing to both provide data and develop the systems to capture the data efficiently.

¹ Transportation Intermediaries Exchange, <http://www.tiexchange.net/locked/introduction.shtml>, accessed January 20, 2005.

² Armstrong & Associates, <http://www.3plogistics.com/3PLmarket.htm>, accessed February 24, 2009

This research is done in collaboration with Coyote Logistics, a third party logistics provider. We demonstrate the value of field research in operations management through an industry collaboration which focuses specifically on the collection and analysis of data in supply chain management to improve operations. Our analysis utilizes past data to find trends that can be projected to change operating policies. We develop a network analysis methodology which facilitates the organization of inherently complex data to extract information in a meaningful way. This methodology is then used to generate operating guidelines. Although the methodology is based on operations in the truckload freight brokerage industry, the analysis can be extended to other brokerage industries.

As a foundation for the network methodology, we make use of recent work in social network analysis, which has examined performance of various organizations. Social network analysis studies the interdependencies among individuals in a given environment with quantitative methodologies based on the network structure of the environment. Networks are defined by a set of nodes, which may represent individuals, and arcs or interconnections between nodes. The arcs represent various forms of communication and/or collaboration between individuals. Researchers have developed metrics to evaluate the position of an individual in a network. For example, centrality measures an individual's connectivity to other nodes throughout the network. In our case, we develop specific metrics that relate operating policies to profitability in spot-market broker operations in supply chain management, which allows us to evaluate existing policies and suggest new policies that can potentially have significant impact especially by accelerating the “learning curve” of newly hired employees.

Section 1.1 presents a review of related literature in freight brokerage operations, as well as relevant work in social network analysis. Section 2 introduces the spot-market operating environment under consideration. Section 3 describes the network analysis methodology in detail.

Section 4 discusses data collection and analysis conducted with our industry partner, including network calibration. Section 5 presents results from an empirical study and includes a discussion of general managerial insights. Finally, Section 6 presents concluding remarks and proposes avenues of future research.

1.1 Literature review

1.1.1 Transportation procurement

There is a wide array of relational structures in which shippers may meet carriers and procure transportation for their loads (Figliozzi 2004). The spectrum varies from vertical hierarchies (where the carrier is internal to the shipper), to the use of long term contracts, to private exchanges, to public spot markets.

The bulk of the transportation procurement literature focuses on long term contracts and the design of related combinatorial auctions. Caplice (1996) studies how the design of an auction can reduce repositioning costs. Ledyard, Olson, Porter, Swanson and Torma (2002) present the first such auction at Sears Logistics which reduced procurement costs by 13% over past practices. Song and Regan (2002) analyze the carriers' perspective showing via simulation that carriers may benefit from such auctions. Benefits from economies of scope (advantages from considering multiple transportation lanes at once) and the ability to easily consider non-price variables (such as level of service) are investigated in Caplice and Sheffi (2003) and Sheffi (2004).

Considerable less work has focused on spot markets which are characterized by many irregular short term transactions. Figliozzi (2004) models the spot market as a series of sequential auctions offered by either a shipper or a set of shippers to a set of carriers. The bidding problem in such

auctions is formulated as an equilibrium and decision theory problem. The study investigates the effect of the auction format, different levels of sophistication for carriers and learning capabilities of the carrier by constructing a simulation.

Figliozi's framework assumes a fixed set of carriers who are notified of each load to be auctioned. In contrast, our framework assumes that brokers choose the carriers to inform of load availability.

1.1.2 Social network analysis

Early work in network analysis focuses on sociological aspects. Granovetter (1973) suggests the use of social networks as a tool to link micro-level interactions to macro-level patterns in sociology. The author introduces the concept of strength of ties as a combination between several sociological factors which characterize an interaction and classifies the tie either as strong, weak or absent. Social networks have perhaps had the largest impact in organizational management in the investigation of the concept of embeddedness (Granovetter 1985, Uzzi 1996 and Uzzi 1997) which suggests that social relationships has a sizable influence on the economic performance of an organization.

Oke, Idiagbon-Oke and Walumbwa (2008) use social network analysis to test hypotheses regarding relationships between different sources of power and the strength of ties between network members in an inter-organizational collaboration network for new product development. Iravani, Kolfal and Van Oyen (2007) use social network analysis in a more operational setting, mapping a supply chain process as a network. They examine the cross-training of customer sales representative at inbound call centers. They show that the network-specific metric of the average

shortest path length is a robust predictor of effective cross-training structure in work sharing networks.

Our work distinguishes itself from previous studies where social network analysis is used in an organizational setting. Based on our observation of freight brokerage activities, we develop a network analysis focusing on the relationships between the brokers and the external carriers, rather than on the internal relationships between the brokers. Thus, in a new application of social network analysis, we examine a network with inter-organizational links and the role of these links on the performance of brokers within one firm.

2. Problem Description

Third-party brokerage companies such as Coyote Logistics operate similarly in many regards. The issues addressed in this paper extend beyond the particular case study presented. We describe the operations of a generic brokerage company, beginning with the introduction of terminology used throughout the paper.

Broker The role of the broker is to find the optimal *vendor* for each open *job*. We assume that a broker works with a fixed set of vendors but has discretion over which jobs to offer each vendor. In the context of freight brokerage, a broker tries to find the best carrier for a shipment. The broker intermediates between the *customer* who tendered the job and the vendor who will serve the job. Often, companies separate brokers who work with customers from brokers who work with vendors. Our work focuses on brokers who work with vendors.

- Job** A job is a commoditized service requested by a *customer* and which must be served by a *vendor*. Jobs may have to be served at specific locations. In this paper, the jobs are shipments of goods, but a job could be any commoditized service from a customer.
- Customer** The customer is the party for whom the *job* is being completed. The customer may be internal or external to the brokerage company. The customer is not an actor in the network model developed in this paper.
- Vendor** A vendor is a company that can provide the services required for a *job*. In the context of freight brokerage, a vendor would be a trucking company, railroad, or other shipping company.
- Inquiry** An inquiry is a request by a *broker* to a *vendor* about a specific *job*. The elements of an inquiry typically include an assessment of the vendor's ability and willingness to serve the job. In the affirmative case, the vendor offers a *quote* to the broker for that job. A negotiation over the pricing terms may follow, and, if both parties are satisfied, a *booking* results.
- Quote** The price offered by a *vendor* to serve a specific *job*.
- Booking** A booking is made when an inquiry is successful and a *vendor* agrees to serve a *job* for the negotiated price.

The generation of jobs is external to the analysis in this paper; we assume a fixed set of jobs for the time period of analysis. In practice, jobs are solicited from customers each day and the set of

available jobs is constantly changing throughout the day. The solicitation of jobs from customers is similar to a vendor inquiry in that it involves an assessment of capability and a negotiation of pricing terms. The optimal solicitation of jobs from customers given the available capacity is an area of potential future investigation and application of this research.

The broker's process of booking loads follows a standard structure and is conveniently compartmentalized into a sequence of calls to vendors. For simplicity, we refer to any form of communication as a call, although actual communication can take the form of fax or email as well. Before each call, the broker must make two decisions – which vendor to call and which jobs to offer to the vendor. A call to a vendor proceeds as follows: for each job presented to the vendor by the broker as an inquiry, the vendor either offers a quote for the job or declines. In the course of the discussion, the broker may present inquiries about additional jobs based on new information indicating potential compatibility of service. For each job for which the vendor has offered a quote, the broker negotiates pricing terms by proposing a counter-offer. The negotiation continues until an agreement is reached or prices are not aligned and both parties are unwilling to change their positions.

This paper addresses the issue of which vendor(s) a broker should contact regarding jobs, and also the broader question of whether the broker – and the company, for that matter – has the right composition of vendors given the set of jobs to serve. We focus on the inquiry step and develop strategies for prioritizing the call order of vendors and the allocation of jobs to vendors for inquiry.

In the absence of guidance, brokers independently develop and refine their strategies for prioritizing vendors and jobs. The tactics employed vary between brokers, but general tactics include:

- Call vendors that are currently seeking similar jobs.
- Call vendors that have expressed interest in similar jobs in the past.
- Call vendors that match characteristics of vendors who have performed similar jobs in the past.

The development of good strategies is key to the performance of a broker, since a broker with poor strategy spends much of his/her time contacting vendors that either cannot serve the job or can only do so for a high price. Therefore, it is important to identify, for any given job, strategies that relate directly to profitability. In our investigation, we develop a methodology that provides such a link, based upon an extensive analysis of existing data. In Section 3, we describe in more detail our model and how the model incorporates the brokers' strategies.

3. Network Methodology

In this section, we present a network model of the interactions between brokers and vendors for a given set of jobs. The goal is to analyze how the number and nature of the interactions translate into profitability for the company. Section 3.1 presents a basic network structure, which is expanded in Section 3.2 to account for the nature of the interactions, which is a key element of the analysis. The networks described in this section capture activities over a fixed period of time for all jobs served during that time across all brokers. The choice of time frame is discussed in Section 4.

3.1 Basic network definitions

The most basic and intuitive network for a set of jobs J is comprised of two sets of nodes N^B and N^V , representing brokers and vendors, respectively, and directed arcs from broker nodes to vendor nodes. The existence of an arc connecting broker i and vendor k indicates that broker i has called vendor k to make inquiries for the jobs in the network. In practice, data are available regarding the number of calls made from broker i to vendor k ; however, data on the specific jobs discussed during a call are often limited to only those jobs that result in a quote. Obtaining detailed information on all jobs discussed is extremely time-consuming for the brokers. Given the time-constrained operating environment, such data collection is not feasible. We discuss the impact of this data limitation in Section 4. Two values are associated with the arcs between brokers and vendors: C_{ik} represents the number of calls between broker i and vendor k within a period which includes all calls made for jobs within the time frame, and Q_{ik} represents the number of quotes vendor k has given broker i (possibly zero). Because an arc does not exist unless at least one call is made, C_{ik} is a positive integer. Since at most one quote is offered for each job, Q_{ik} is a non-negative integer less than or equal to $|J|$. Note that because a call may elicit multiple (or zero) quotes, Q_{ik} can be larger or smaller than C_{ik} .

Insert Figure 1 here

Figure 1 depicts a small example of a network in which two brokers placed calls to and received quotes from four vendors for three jobs during the time horizon of analysis. The data records presented on the left side of the figure are represented in network form on the right side of the figure. Broker 1 called Vendors 1 and 2, and Broker 2 called Vendors 3 and 4. These calls are represented by the existence of arcs between the brokers and vendors. The arc values between brokers and vendors illustrate the number of calls and the quotes received as a result of these calls.

From this network we can construct several metrics. We define the *broker contact set* $\Gamma(i)$ as the set of vendors that are adjacent to broker node i in N^B . The *broker connectivity* metric, κ_i , is the cardinality of $\Gamma(i)$, denoted as:

$$\kappa_i = |\Gamma(i)|.$$

Thus, κ_i measures the number of unique vendors contacted by broker i in N^B . Clearly, we have $0 \leq \kappa_i \leq |N^V|$.

The *broker call* metric, Ψ_i , measures the total number of calls made by broker i and is defined as:

$$\Psi_i = \sum_{k \in \Gamma(i)} C_{ik}.$$

The *broker quote* metric, Θ_i , measures the total number of quotes made to broker i and is defined as:

$$\Theta_i = \sum_{k \in \Gamma(i)} Q_{ik}.$$

Since each vendor can (theoretically) offer quotes for all jobs, we have $0 \leq \Theta_i \leq \kappa_i |J|$. We also measure the *density*, θ , of broker i which is the ratio of the two aforementioned metrics:

$$\theta_i = \Theta_i / \kappa_i.$$

The density metric represents the average number of quotes a broker obtains per vendor contacted. Theoretically we have $0 \leq \theta_i \leq |J|$, but in practice θ_i is much smaller than $|J|$, since typically a broker contacts multiple vendors who are suitable only for a subset of the total jobs that a broker works during the time period. Therefore, the broker is not likely to receive a quote on every job from every vendor contacted.

3.2 Enhanced network

The network described in Section 3.1 is limited since there is no mechanism to distinguish which vendors are more apt to serve a job, an essential step towards determining how interactions

translate into profit. To address this concern, we first identify candidate conditions for contacting a particular vendor for a given job, which capture the vendor's affinity to work with the brokerage company and the vendor's capacity to serve the job. These conditions yield the likelihood that a vendor would offer a quote if contacted by a broker and that the quote would be desirable to the broker. We consider Boolean conditions; i.e., each condition is either true or false. Examples of candidate conditions are presented in Section 2, such as calling a vendor currently seeking similar jobs.

In addition to identifying the candidate conditions, it is important to consider *combinations* of the conditions. This allows for a more refined classification of broker-vendor interactions, which in turn translates into a more accurate quantification of the relationship between those interactions and profitability. For example, one combination could be “the vendor has served similar jobs before, but does not have staff/equipment available at the job's location,” while another could be “the vendor has staff/equipment available at the job's location, but has never served similar jobs before.” The analysis of the data facilitates the determination of condition combinations – which can be thought of *contact strategies* – that are more desirable for the company from the perspective of profitability, thus providing a guide for future interactions.

To represent contact strategies in the network, we add a set of nodes N^S , representing *strategy bins*. Each strategy bin represents a combination of the candidate conditions, including the *null bin* where none of the candidate conditions are satisfied. Since candidate conditions are Boolean, a total of n conditions would yield 2^n strategy bins; for example, five conditions yield 32 bins. Clearly, even for moderate values of n , the total number of bins can be excessively large. The number of data points per bin decreases with the number of bins; when the number of bins is too large, it is not possible to draw meaningful conclusions due to lack of data points for individual bins. To circumvent the problem, one can tier some of the conditions, grouping conditions that

are true only if another one is also true. For example, if conditions A , B and C can be tiered, then there are four (rather than eight) possible combinations – namely, (i) A is true, (ii) A is false but B is true, (iii) A and B are false but C is true, and (iv) A , B and C are false. Creating such a tier system – which, in our case, was natural given the nature of the candidate conditions – can drastically reduce the number of strategy bins.

Because the list of strategy bins is exhaustive and mutually exclusive, each vendor must match exactly one strategy bin for each job. We replace the broker-vendor arcs with two new arc sets. An arc from broker i to bin j is assigned a value Y_{ij} representing the number of quotes broker i received from vendors that matched strategy bin j during the time horizon of analysis. Notice that, by construction, Y_{ij} partitions the number of quotes broker i receives by strategy bin and hence we must have

$$\sum_{j \in N^S} Y_{ij} = \sum_{k \in \Gamma(i)} Q_{ik} = \Theta_i \quad \forall i \in N^B .$$

An arc connecting vendor k to bin j is assigned a value Z_{kj} representing the number of jobs for which vendor k matched strategy bin j . For carrier k , Z_{kj} partitions the job set J and thus we have:

$$\sum_{j \in N^S} Z_{kj} = |J| \quad \forall k \in N^V .$$

For a given strategy bin j , the summation of Y_{ij} across all brokers can be seen as the number of quotes captured from that strategy while the summation across all vendors can be seen as the number of potential quotes from that strategy. It is worthwhile noticing that the enhanced network is constructed from information pertaining to individual jobs (i.e., the network is *job-oriented*); thus, metrics regarding calls are not included, since as discussed earlier job-specific call data are in general not available.

Insert Figure 2 here

Figure 2 illustrates the enhanced network for the example introduced in Figure 1. Here we introduce three strategy bins. The data records on the left include the quote record from Figure 1

as well as the vendor-job relationships which display which strategy bin each vendor matched for each job. For a broker i , each time a quote is received from a vendor for a job, the quote information is cross-referenced in the vendor-job relationship table, so that the quote can be assigned to a strategy bin. Summing over all quotes yields the value of Y_{ij} between the broker and strategy bin. The value for the arc between vendor k and strategy bin j , Z_{kj} , is calculated by counting the number of times strategy j appears in the vendor k row of the vendor-job relationship table.

3.2.1 Offer potential metric

The addition of strategy bins leads to another metric. The *offer potential* metric ω_{ij} , defined for each broker i and strategy bin j , is the ratio of the number of quotes to the potential number of quotes of that bin for a specific broker. Formally,

$$\omega_{ij} = Y_{ij} / \sum_{k \in \Gamma(i)} Z_{kj} .$$

The summation in the denominator is taken over $\Gamma(i)$, the set of vendors called by the broker. Note that $0 \leq \omega_{ij} \leq 1$. When the vendors are “partitioned” among the brokers; i.e., when the set of vendors contacted by each broker are mutually disjoint, the offer potential metric quantifies the success of the broker in mining the potential available from a given strategy.

If vendors are not partitioned among brokers, the offer potential metric retains its meaning, but may be complicated due to competition between brokers and thus must be looked at in conjunction with other metrics. For example, suppose there are n brokers, n jobs and n vendors, and suppose that there is only one strategy bin (in addition to the null bin). If each vendor matches the strategy for a single distinct job and each broker working on a distinct job calls all the vendors (and eventually receives a quote), then $\omega_{ij}=1/n$ for all i . Clearly, this number can be

arbitrarily small, even though the brokers achieved the maximum number of quotes in a collective sense. In such an example, there may be more brokers in the firm than necessary; however, it is important to note that ω_{ij} alone does not convey that information. For example, with a setting similar to the one just described, assume that there is a single broker who handles all n jobs. If that broker is an ineffective negotiator and gets only one quote, then again we have $\omega_{ij}=1/n$, but for a different reason. Note that the metric for a broker only shows the percentage of the potential mined from the strategy but does not say anything about the *quality* of that strategy. If a strategy is profitable, a high value of ω_{ij} is desirable; however, if the strategy is not profitable, then achieving a high value of ω_{ij} is less desirable. We discuss this issue in Section 3.2.2.

3.2.2 Measuring the quality of the strategies

Recall that the goal is to analyze how the number and nature of the interactions between broker and vendors translate into profitability for the company. Although the creation of the strategy bins allows for differentiation between the vendors, the network does not evaluate the benefit of using a given strategy, in terms of its impact on profit. To rectify this, we associate *weights* with the strategy bins, giving higher weight to strategies that are more desirable. The bin weights are defined as:

$$w_j = P_j / E_j ,$$

where

P_j = Total profit from jobs served by vendors matching strategy j

E_j = Effort spent by all brokers on using strategy j across all jobs.

The weights account for not only the profit generated by a strategy but also the effort required to obtain the quotes – a profitable strategy that requires an excessive amount of brokers' time to

contact vendors may be less desirable. It is difficult to measure the value of E_j given the limited data available. Recall that recorded call information contains limited job-specific information. Section 4 presents proxies for the value of E_j , which can be constructed from the available data.

With the bins weights, we define new broker metrics: the *weighted quote*

$$\Theta_i^w = \sum_{j \in N^s} w_j Y_{ij}$$

and the *weighted total offer potential*

$$\Omega_i^w = \sum_{j \in N^s} w_j \omega_{ij} .$$

As shown in the empirical study presented in Section 5, the weighted metrics are better indicators of the broker's performance than the unweighted metrics.

4 Data Collection Methodology

Given our collaboration with Coyote Logistics, we were able to obtain the data needed to calibrate and test the network analysis methodology introduced in Section 3. We discuss now some specific steps we have taken to manipulate the data. During the solicitation process, Coyote Logistics records information about broker activities which is stored in a company database. The information includes the vendors called over a period of time, the candidate conditions that hold for a vendor for a particular job, and the vendor assigned to each job, along with the final negotiated price. Note that the data on candidate conditions allow for the construction of the strategy bins introduced in Section 3. Quotes made by other vendors for a job may be recorded but not all quotes are necessarily entered by the brokers. Our study focuses on data collected over the period of January 1, 2008 to August 28, 2008.

4.1 Network decomposition

The Coyote Logistics database is quite comprehensive due to the scale of their operations. Therefore, to address complications due to the large volume of data, the job set J is partitioned into smaller sets. Smaller job sets make data collection and metric calculation easier. Note that, since the enhanced network of Section 3.2 is job-oriented, we can decompose it across jobs. More specifically, we partition J into subsets J_d which contain all jobs served on the date d . After partitioning jobs, the information regarding the jobs in J_d is processed to determine metric values – e.g., the number of quotes a broker received from a specific strategy bin. Once processed, the arc values and metrics from the disaggregated networks are added to yield the corresponding information on the original job set J .

Note also that the basic broker-vendor network described in Section 3.1 and the metrics dependent on them are *not* decomposable by jobs; thus, the number of calls C_{ik} , the contact set $T(i)$, the connectivity κ_i , and the unweighted and weighted offer potential metric, ω_{ij} and Ω_i^w must be recalculated after the data has been re-aggregated based on the initial data.

The separation of the jobs into the days they were served provides the benefit of a natural way to separate the data for calibration and testing. To avoid a seasonality bias, the jobs that were served on odd numbered dates from January 1st to August 31st were used for the determination of the bin weights. Those weights were used with the data from even numbered dates for the analysis.

4.2 Estimation of effort

The unweighted metrics can be calculated from the available Coyote database. However, the bin weightings require a quantification of effort spent on a strategy, E_j . As mentioned in Section 3, there is no record of which inquiries a broker made during a call to a vendor. In what follows, we discuss the assumptions, data processing and approximations necessary to estimate E_j , and introduce two approaches to approximate the effort.

The first proxy, E_j^+ , uses the assumption that all vendors called during a fixed time frame prior to the day a job was served receive an inquiry about the job. This is an overestimation as not all jobs are presented as an inquiry when a broker calls a vendor. We define E_j^+ as follows. If vendor k was called by any broker during the time horizon of analysis, we add the value Z_{kj} to strategy bin j , representing the number of jobs in bin j matched by vendor k :

$$E_j^+ = \sum_{i \in N^B} \sum_{k \in \Gamma(i)} Z_{kj} .$$

As stated before, E_j^+ overestimates the amount of effort exerted. The overestimation can have large impacts on some strategy bins. If the strategy occurs frequently, to the extent that a broker could not feasibly call all vendor nor would such effort be necessary, the value of E_j^+ will be very large, driving the weight of the bin to 0.

The second proxy, E_j^- , counts the number of quotes received for each bin, and is defined as

$$E_j^- = \sum_{i \in N^B} Y_{ij} .$$

This underestimates the amount of effort dedicated to the strategies since Y_{ij} represents only calls that yield a recorded quote; i.e., calls that do not yield a quote and quotes that are not recorded in the database are absent in the calculation. This effect from the underestimation can be compounded when a strategy that rarely generates a quote presents desirable profits when quoted;

under this proxy for E_j , the weight of these bins will be artificially inflated and the strategy seems more important than it actually is.

5 Empirical Study

The first part of the empirical study focuses on the evaluation of the network analysis model. In particular, we assess the ability of the network analysis model to predict profitability as a function of the network metrics introduced in Section 3. Further, we examine the value of adding and weighting the strategy bins in the network analysis (i.e., comparing Figures 1 and 2). The second part of the empirical study uses the network analysis model to provide general managerial insights for brokerage operations. In particular, we use the model to develop operating policies and evaluate the performance of brokers.

As mentioned earlier, the network analysis model can aggregate data for any fixed period of time. The results presented in this section analyze data for jobs that were served on even dates between August 2nd and August 28th. To avoid disclosing proprietary information, numbers have been scaled where necessary.

5.1 Model evaluation

In the basic network model, presented in Figure 1, we quantify the activities of each broker i in N^B with the number of calls, Ψ_i , the number of quotes, Θ_i , and the connectivity, κ_i . We compute from the latter two values the density of broker i , θ_i . Table 1 presents regression results for these four metrics against the profitability of the broker for 88 brokers.

Insert Table 1 here.

Observation 1: *The information in the basic network does not predict profitability well.*

The regression results in Table 1 display a weak increasing trend between profitability and the number of calls a broker performs; that trend is stronger when the number of quotes is the independent variable. This is to be expected as, if all jobs and vendors were equal, more calls and more quotes should translate into more bookings and profit. However, the low R-square values mean that the metrics cannot be used as powerful predictors of profitability.

Somewhat surprising is that the connectivity is (albeit poorly) negatively correlated with profitability, as indicated by the negative sign of the t-statistic. This suggests, along with the positive correlation of the density metric, that a larger stable of vendors to call is not necessarily beneficial and that there are brokers who are benefitting from contacting a more selective set of vendors.

The enhanced network model, presented in Figure 2, introduces strategy bins. These bins are weighted by dividing the profit yielded from the bin by the effort exerted in utilizing the bin, E_j . However, as discussed in Section 4, measuring the effort in utilization of a strategy bin is difficult given available data. Therefore, we use two proxies to estimate the effort: the number of quotes received from carriers matching a bin for a given job (E_j^-), which underestimates the effort, and the number of potential jobs for which contacted vendors match a bin for a given job (E_j^+), which overestimates the effort. We present our analysis of the two proxies in Table 2.

Insert Table 2 here.

The empirical tests evaluate the extent to which weight estimates potential. The weights are used in the two strategy metrics – the weighted quote, Θ_i^w , and the weighted offer potential metric, Ω_i^w .

Table 2 presents the regression results for the two weighted broker metrics under the two different weights against profitability of the broker for the same 88 brokers.

***Observation 2:** The profitability of a broker is better predicted by weighting the number of quotes received than considering the unweighted number of quotes.*

The regression results for the two weighted quotes show a sizeable improvement over the results using an unweighted number of quotes in Table 1 in correlation and significance. This supports the modeling decision of classifying the jobs into separate strategies.

The two weighted offer potential results show a positive correlation with profit. Like the density metric, the weighted offer potential metric is to be used in a supporting role in the evaluation of brokers.

***Observation 3:** Estimating the effort of utilization of a strategy bin by potential jobs rather than quotes leads to better predictive ability.*

Looking at the two weighted quote rows (since they are the powerful predictors), it is noteworthy when comparing the two sets of bin weights that estimating effort by potential jobs, E^+ , outperformed estimating effort by quotes, E^- . This contrasts with the conclusion from Table 1 that quotes are a better predictor of profit than either calls or connectivity. A possible reason may be due to the type of errors that the proxies for effort introduce: Deriving the weights from quotes may artificially inflate the weight of some bins and deriving weights from potential jobs may punitively drive the weight of some bins to zero. It is possible that having mediocre bins with high weight is more misleading than ignoring those bins altogether. The weights generated by measuring effort by the potential jobs are used hereafter.

The regression results in this subsection validate the use of the network model to evaluate profitability. The results demonstrate how the addition of the strategy bins significantly improves the information regarding broker vendor interactions over what may otherwise be obtained. We show that we are able to quantify the relationship between broker and vendor interactions with company profit despite complications that arise from the difficulty in collecting all the desired data. The results also suggest that the effort proxies provide reasonable approximations given that the true data can not be feasibly obtained during real-time operations.

5.2 Managerial insights

5.2.1 Operating policies

The network analysis methodology provides valuable insights into the design of operating policies to optimize broker activities in soliciting offers from vendors. As the analysis in Section 5.1 indicates, brokers are more likely to generate higher profits when they selectively call vendors based on a combination of job-specific conditions, rather than simply increasing the absolute number of calls made for a job. The relative weightings of strategy bins provide guidelines for brokers to select vendors to call for a specific job. Such guidelines may increase profit by choosing vendors that are better suited for certain jobs.

The network analysis model can also facilitate more strategic decisions. For example, the model can project the changes in profitability as either the number of brokers or the number of vendors in the network increases. Rather than simply increasing the absolute number of vendors, by evaluating the quality of the strategy bins and the current characteristics of jobs solicited, a company can seek new business from vendors with certain attributes.

It is important to note that because the weights of the bins are constructed from data that is affected by the behavior of the brokers, changes to operating policies may affect the effectiveness of a strategy. This is true because even within a strategy, not all jobs are equal, and after a certain threshold, jobs strategies will be less effective than what is suggested by its weight. For this reason, it is suggested that the network analysis be regenerated periodically so that the weights may reflect current behavior.

Lastly, the information generated from the network analysis can provide feedback in the solicitation of jobs. Given the network of available vendors, brokers who work with customers soliciting jobs can assess the potential profitability of a job in advance of pricing the job. A job that does not have many vendors that could serve the job effectively should command a lower price.

5.2.2 Evaluating brokers

The metrics introduced in Section 3 provide a means to evaluate the performance of brokers. Brokers can be evaluated relative to other brokers within the company, or relative to their own performance over time. Table 3 presents an analysis of four brokers, classified by their tenure at the company as of August 2008. Both metrics independent of strategy bins and those dependent on strategy bin are listed for each broker. Column 1 displays the number of calls made by the broker during the time horizon of the study, Ψ_i ; column 2 displays the connectivity of the broker, κ_i ; column 3 displays the number of quotes received, Θ_i ; column 4 lists the density metric, θ_i ; column 5 displays the weighted offer potential metric, Ω_i^w ; column 6 displays the weighted quote metric, Θ_i^w ; and column 7 displays the profit earned by the broker.

Insert Table 3 here.

Brokers A and B were hired only two months before the analysis, and Brokers C and D were hired two years prior to the study. As expected, the veteran brokers achieved significantly higher profits. However, a deeper analysis of their metrics provides interesting observations about performance which can be used to guide new broker training and continual performance review.

Consistent with Observation 1, the profitability of a broker cannot be predicted solely on the number of calls. For example, Broker B made far more calls than Broker A, yet Broker A has double the profitability. The same statement can be made in a comparison between Broker C and Broker D. Also while the relative ranking is preserved, extrapolating the number of quotes proves to be a weak predictor of profitability in these examples. Conversely, and anecdotally supporting Observation 2, the weighted number of quotes acts as a reasonable predictor of profit.

By comparing Brokers C and D to Brokers A and B, it would seem that the veterans far outperform the new hires. The veterans appear to be more selective in their interactions by vendor, as evidenced by their higher density metric, compared to the new hires. It is thought that over time the brokers internalize the guidelines suggested in Section 5.2.1 learning over time which strategies are effective even if strategy bins are not explicitly stated.

Making the guidelines explicit can be valuable in the training of new employees and accelerate the learning curve of new hires. Estimates from Coyote Logistics suggest that a two-week acceleration in the learning curve can improve per broker internal rate of return by 11%.

Observation 4: *No single metric contains all information about broker performance. It is important to consider a composite picture of metrics.*

In addition to training guidelines, a composite of the metrics may be used to obtain additional insight. Table 4 presents analysis on an additional two brokers which illustrate how the metrics may be used to generate a better picture to evaluate a broker's performance than just the use of profit.

Insert Table 4 here.

Brokers E and F have been with the company 4 and 3 months, respectively. In comparison to the new hires in Table 3, both brokers show an improvement in profitability echoing the suggestion that even a small acceleration to the learning curve may have great benefits. A pairwise comparison between the two supports the observations in the pairwise comparisons in Table 3. However, if we compare Brokers C and E we notice that Broker E, despite having a slightly lower weighted quote metric than Broker C, was more profitable. However, Broker E does have a higher density and weighted offer potential metric. After a little more investigation, it emerges that among brokers with a comparable weighted quote metric, Broker C has lower density metric, weighted offer potential metric and profitability. It suggests that Broker C is not capturing the full potential of the vendors he contacts and that there is room for further improvement in his/her performance.

Explicit guidelines on which strategies to choose can also be used to improve retention of brokers who are strong negotiators but are not proficient in choosing vendors to call. Broker F, while achieving higher profit than the new hires in Table 3, has a relatively low weighted quote metric compared to his peers. However his weighted offer potential metric is unusually high. This suggests that while this broker is gleaning the potential that is available, there is not much *total* potential available to him/her; the broker is calling vendors which do not match well to the set of jobs that are available.

The anecdotal data in this subsection support our conclusions about the metrics' predictive effectiveness from Section 5.1. Furthermore, these examples support the claim that a small acceleration to a broker's learning curve can have a large impact; this motivates the use of the network analysis to design operating policies for a broker's activity. Additionally, the data provide a couple of examples that illustrate how a composite of the metrics may be used to expose circumstances or behavior that may not be detectable when examining only one metric.

6 Conclusions

This paper presents a network analysis model to study business processes for a third-party intermediary and introduces a series of new performance metrics. The model and metrics are calibrated and validated with data from industry. The network analysis is then used to design operating policies to optimize broker activities. Implementation of the policies suggested by the network analysis is scheduled to begin in spring 2009.

Future research can expand the network analysis to job solicitation operations in which brokers solicit jobs from customers. The general approach should be valid; however, new strategy bins will be required, along with new calibration and validation of the model. Additionally, as mentioned in Section 5, combining models from both the vendor and customer sides of the business can provide valuable feedback on the type of jobs to solicit and vendors to contact.

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	R Square	F	t-statistic	P-value
Calls, Ψ_i	0.1958	20.943	4.5764	1.58E-05
Quotes, Θ_i	0.5612	109.99	10.4875	4.71E-17
Connectivity, κ_i	0.0878	8.280	-2.8776	.00505
Density, θ_i	0.3422	44.744	6.6891	2.16E-09

Table 1: Profit predictions from initial network

	R Square	F	t-statistic	P-value
Weighted Quotes Θ_i^w with E ⁻	0.6576	165.138	12.8506	1.02E-21
Weighted Quotes Θ_i^w with E ⁺	0.7388	243.195	15.5947	8.52E-27
Weighted Offer Potential Ω_i^w with E ⁻	0.2148	23.521	4.8498	5.44E-06
Weighted Offer Potential Ω_i^w with E ⁺	0.2025	21.839	4.6732	1.09E-05

Table 2: Profit predictions from enhanced network

		Metrics independent of strategy				Strategy dependent metrics		Profit
Tenure		Ψ_i	κ_i	Θ_i	θ_i	Ω_i^w	Θ_i^w	
<i>New Hires</i>								
Broker A	2 mon.	3,872	2,150	50	0.023	96.38	536.11	2,537.55
Broker B	2 mon.	5,784	4,026	42	0.010	41.08	205.87	1,142.06
<i>Veteran employees</i>								
Broker C	2 years	4,428	1,280	134	0.104	74.89	1,641.28	7,286.74
Broker D	2 years	3,776	304	162	0.532	132.86	2,295.35	14,828.22

Table 3: Broker productivity analysis

		Metrics independent of strategy				Strategy dependent metrics		Profit
Tenure		Ψ_i	κ_i	Θ_i	θ_i	Ω_i^w	Θ_i^w	
Broker E	4 mon.	3,972	602	110	0.182	95.78	1,354.51	10,998.03
Broker F	3 mon.	3,850	1,792	90	0.050	122.83	702.27	3,782.18

Table 4: Broker productivity analysis

Broker call record

	Broker 1	Broker 2
Vendor 1	1	0
Vendor 2	1	0
Vendor 3	0	1
Vendor 4	0	2

Quote record

Broker 1	Job 1	Job 2	Broker 2	Job 3
Vendor 1	1	1	Vendor 1	0
Vendor 2	0	1	Vendor 2	0
Vendor 3	0	0	Vendor 3	0
Vendor 4	0	0	Vendor 4	1

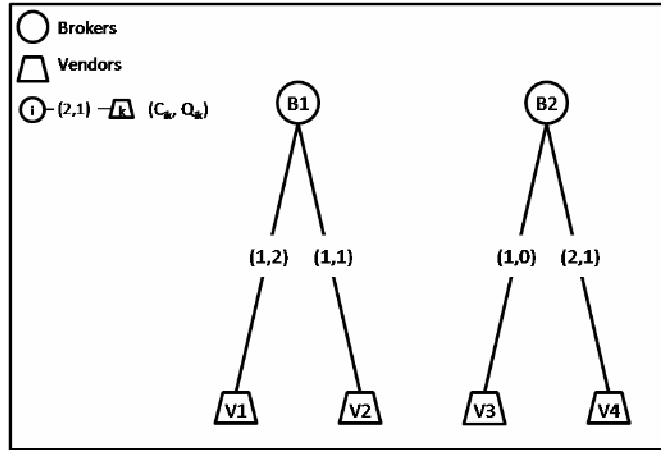


Figure 1: Basic broker-vendor network

Quote record

Broker 1	Job 1	Job 2	Broker 2	Job 3
Vendor 1	1	1	Vendor 1	0
Vendor 2	0	1	Vendor 2	0
Vendor 3	0	0	Vendor 3	0
Vendor 4	0	0	Vendor 4	1

Vendor / Job relationships (Bin type):

	Job 1	Job 2	Job 3
Vendor 1	S1	S1	S1
Vendor 2	S1	S2	S2
Vendor 3	S1	S2	S3
Vendor 4	S3	S3	S2

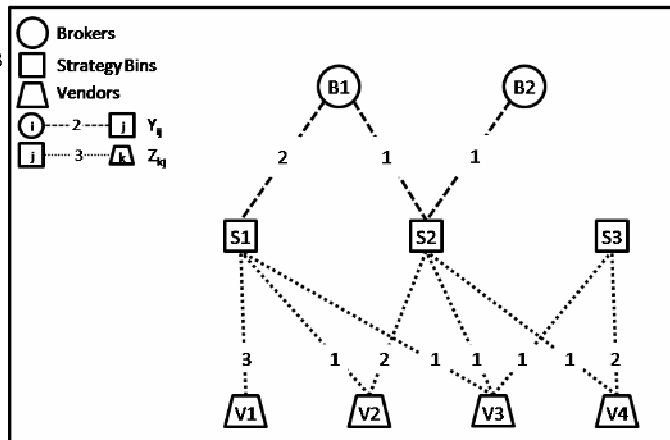


Figure 2: Enhanced network