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Total Hockey Optimizes Omnichannel Facility Locations

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Abstract. Omnichannel distribution, which blends brick-and-mortar retailing and e-commerce, is a key challenge for today's supply chains. In this paper, we report on a study to design an omnichannel distribution system for Total Hockey, a growing U.S. sporting goods retailer in a competitive environment. Management strongly believes that e-commerce success will depend on high service levels characterized by one- or two-day delivery and initially thought that a new omnichannel warehouse located on the East Coast could support its expansion plans. To study the situation, we developed a profit-maximizing optimization model for locating omnichannel warehouses that supports both e-commerce and store shipments. The model uses estimates of e-commerce demand by metropolitan statistical area (MSA) across the United States, while incorporating management's sales expectations regarding the value of high service levels, e-commerce sales lost to competitors' stores, and reverse cannibalism from Total Hockey's own retail stores. Multiple warehouse sizes allow modeling of nonlinear inventory costs. The facility-location optimization model allows exploration of multiple solutions and an assessment of the impact of higher service levels. The results of the study were contrary to management expectations and suggested a significant redesign of the distribution system. We report results for several analyses, implementation details, and managerial insights for omnichannel distribution.

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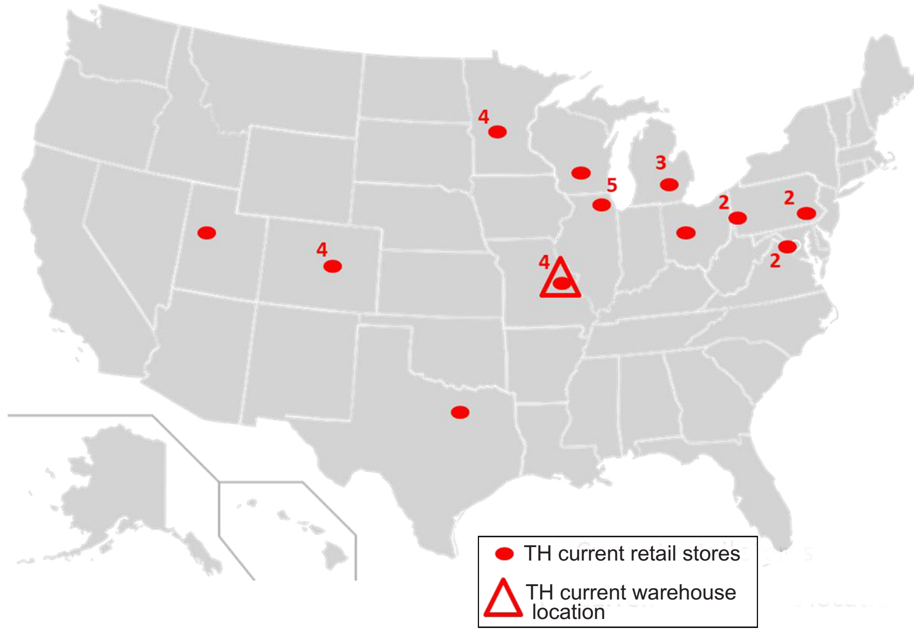
Keywords: omnichannel • e-commerce • facility-location modeling • integer programming • linear programming • OR/MS implementation: applications

The need to design (and redesign) distribution systems to facilitate omnichannel commerce and ensure high service levels is a popular topic in both the business world and academia (e.g., Swaminathan and Tayur 2003, Agatz et al. 2008, Chao and Norton 2016, Ishfaq et al. 2016, Zhang et al. 2016). While multiple channel refers simply to selling through multiple channels, such as phone (including mobile), Internet, catalogs, and brick-and-mortar retail stores, omnichannel distribution focuses on using an integrated logistics system to support the multiple channels, and often integrates front-end (sales) and back-end (logistics) systems (Hübner et al. 2016). Omnichannel distribution differs from multiple-channel distribution where, for example, two separate warehouse and distribution systems are used to satisfy retail store replenishment and e-commerce direct-to-consumer shipments in parallel.

This paper reports on a study for Total Hockey (TH), a hockey equipment brick-and-mortar and e-commerce retailer that sought to locate omnichannel warehouses to support a retail network and e-commerce sales across the United States. A key focus is on e-commerce sales and how they are likely to be influenced by higher service levels (i.e., faster delivery times) from new warehouse locations.

At the beginning of the study, TH operated 30 stores in 11 states, all served from a single warehouse in St. Louis (Figure 1). The warehouse stocked approximately 32,000 stock-keeping units (SKUs) to support both the retail stores and e-commerce orders; provided break-bulk functions for the inbound container and full truckload shipments from manufacturers; and picked, packed, and shipped e-commerce orders. TH also used retail store inventories to satisfy e-commerce orders

Figure 1. (Color online) At the Start of the Study, TH's 30 Retail Store Locations Were Primarily Across the Upper Midwest



Note. The numbers indicate multiple stores in a city; for example, Chicago has five stores.

in two cases. The first case was for inventory at the retail stores in St. Louis, which are located near the warehouse. Each day, a peddle truck delivered items from the warehouse to the stores to replenish store inventories. That truck also collected items from the stores to take back to the warehouse, possibly combined these items with items from the warehouse or other stores into a single shipment, and used them to fulfill e-commerce orders. TH developed this inventory-pooling approach to reduce split shipments and backorders. It reflects their relatively high SKU count, which includes a large number of low-unit-volume items and the small average order size of 2.7 items per order. The second case of using store inventory for e-commerce orders occurred when an item was not available in the St. Louis warehouse or a St. Louis store, in which case the item was shipped to the customer directly from the store closest to that customer. However, this practice can create split shipments, which add shipping costs and require stores to dedicate backroom space for packing and shipping operations. Because TH stores are generally in expensive retail areas, the company prefers to minimize its backroom space for packing and shipping, to maximize retail floor selling space. In practice, each retail store typically stocks only a fraction of the SKUs TH sells, depending on factors such as local demand, available space, or availability of stock from other nearby stores; shipping items directly from stores to customers is discouraged. Thus, most e-commerce orders are sent from the St. Louis warehouse.

This paper reports on our study to redesign TH's distribution system to serve 359 U.S. metropolitan statistical areas (MSAs) using an omnichannel warehouse location model. We provide empirical results that support findings in the channel selection literature and incorporate management requirements in the model in a way that supports TH's decision-making process (Levasseur 2015). Important aspects of TH's situation, which add complexity in our study, are: (1) TH's aggressive expansion plans, (2) a focus on the impact on e-commerce demand in an MSA both from offering high service levels (one- or two-day delivery) and from the presence of competitor stores and TH stores in the MSA, (3) the lack of MSA-specific data on e-commerce market sizes for hockey equipment, and (4) the use of retail store inventories for e-commerce orders.

The *Background* section includes relevant background on TH and a brief review of the omnichannel modeling literature. In the *Modeling Market Share* section, we describe our work with TH management to estimate demand parameters, and to model warehouse and inventory costs that are inputs to the facility-location optimization model. In *Multiple-Facility-Location Model*, we present the location model, and in *Analysis of Solutions*, we analyze the results, including the important role of pooling store and warehouse inventory. We discuss TH management's decision and implementation issues in *Management Decision and Implementation*, and follow with concluding remarks in *Conclusions*.

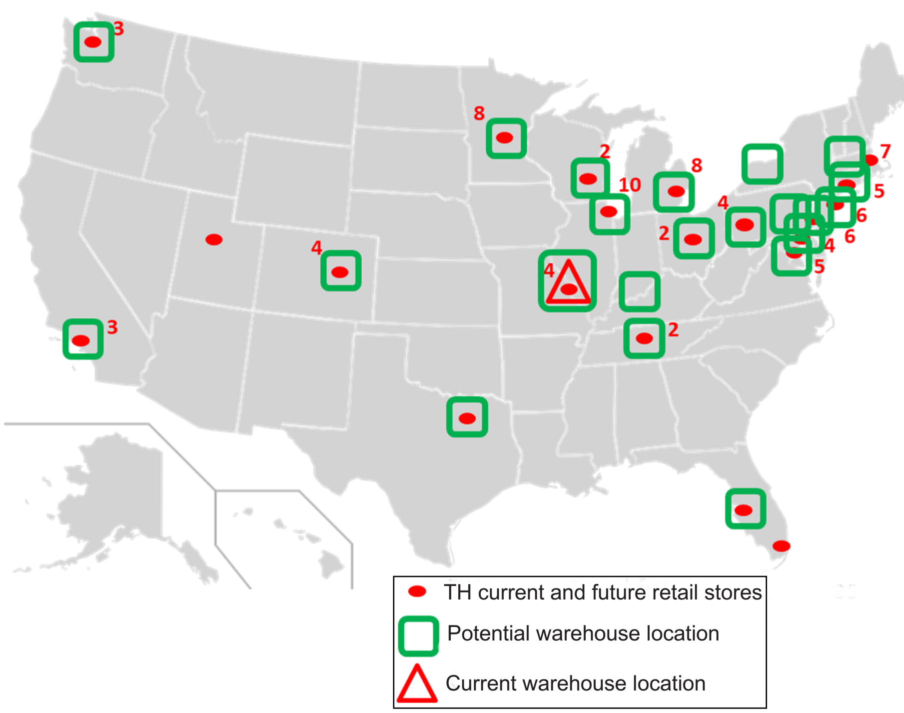
Background

Background on TH

TH grew very rapidly, both organically and through acquisitions, since being founded in the Midwest almost 20 years ago. It initiated online sales in 2002; these sales currently constitute approximately 30 percent of its revenues and have been growing strongly. In 2013, TH initiated an omnichannel strategy with all inventory items visible on its e-commerce website. When an e-commerce order is received, TH's omnichannel software gives priority to using a single shipment for all the items included; so, most orders are sent as a single shipment from the St. Louis warehouse (using items from the warehouse and possibly the St. Louis stores). At the time of our study, TH had aggressive five-year expansion plans to increase from 30 retail stores, mostly in the Midwest (Figure 1), to 86 stores across the United States by adding 29 stores in the Northeast, 18 stores in the upper Midwest, and several stores in Florida, Los Angeles, and Seattle (Figure 2). TH believes these new stores will increase e-commerce sales in the new regions from reverse cannibalization. Expansion into the hockey-rich Northeast, which has numerous competitor stores but very few TH stores, required us to consider the effect of both the new TH stores and competitors' existing stores on TH's e-commerce market share.

TH's CEO held a strong view that one-day (or same-day) delivery of many consumer goods, as companies such as Amazon, Google, and Ebay demonstrate, without requiring the customer to pay for premium shipping, would drive customers to expect similar high levels of service (Smith 2014). Therefore, TH expects to gain market share of e-commerce demand by positioning larger amounts of inventory close to the larger markets, which include the Northeast, Chicago, Minnesota,

Figure 2. (Color online) TH's Planned Retail Store Locations and the Potential Warehouse Locations Are Scattered Across the United States



Note. The numbers indicate multiple stores in a city; for example, 10 stores are planned in Chicago.

and Detroit. This focus on service is driven by the fixed uniform pricing arrangements of the major equipment suppliers, which require all retailers to sell at or above a specified price. Thus, product availability and delivery time, not price, are the key differentiators. Therefore, we needed to incorporate shipping time from the warehouse when modeling TH's e-commerce market share of an MSA. We also needed to estimate the e-commerce hockey-equipment market size by MSA, because these data were not available. The U.S. hockey-equipment retail business is dominated by eight small privately held retailers that operate brick-and-mortar retail stores and e-commerce sites. These competitors do not share data on their e-commerce market size in each MSA.

Prior to our study, TH was tentatively planning to add an omnichannel warehouse near Philadelphia, Pennsylvania to support the new retail stores and expected growth in e-commerce business in the Northeast. The company was also interested in options that would allow it to open small warehouses near each major market to provide customers with one-day delivery. However, our study provided a more general profit-maximizing, optimal network design that considered 23 potential warehouse locations across the United States.

Literature on Omnichannel Modeling

One key concern in the omnichannel research literature is the channel selection decision of whether to fulfill e-commerce orders from dedicated e-commerce warehouses (or fulfillment centers), the same warehouses that support retail stores, retail store inventories, or a combination of these sites. Researchers have addressed how the use of these different e-commerce channels is impacted by inventory pooling, demand correlations, postponement, options for in-store pickup, relative costs, and the percentage of total sales through e-commerce (Alptekinoğlu and Tang 2005, Chiang and Monahan 2005, Bendoly et al. 2007, Mahar and Wright 2009, Bretthauer et al. 2010, Gallino and Moreno 2014, Torabi et al. 2015). Results from Bendoly et al. (2007) show how the use of a dedicated e-commerce channel depends on the percentage of total demand that is e-commerce, the relative costs, the level of demand variation across customers (markets), and the number of retail stores. Theoretical total-cost models show that the benefits from using retail store inventories generally decrease with the number of stores and with the percentage of demand that is e-commerce. However, the use of retail stores for fulfillment appears to be growing, and a recent study (Griffin-Cryan and Wall 2015) suggests over 80 percent of leading retailers either already offer, or plan to offer, e-commerce fulfillment from retail stores. Ishfaq et al. (2016) note that the role of stores is evolving toward serving both in-store and online customers.

Our research bridges the gap between channel-selection issues for omnichannel commerce and optimization models for competitive location and network design. Only a few researchers address locational aspects of omnichannel distribution. Bretthauer et al. (2010) show that the number of e-commerce fulfillment locations changes with the percentage of e-commerce orders, but they do not consider specific locations. Liu et al. (2010) use a capacitated location optimization model to solve artificially generated two-echelon problems and explore the trade-off between inventory pooling effects and transportation costs, but do not use real-world data or include competition. Zhang et al. (2016) provide a multiple-objective capacitated distribution-network-design model that allows shipments through different channels involving a manufacturer, central distribution centers (DCs), and regional DCs. While multiple channels are integrated in one optimization model, total demand is given and there is no differentiation of customers (e-commerce versus retail stores).

In contrast to these works, our research includes location modeling based on TH's demand data and costs, competition to determine e-commerce market share, and reverse cannibalization between TH's e-commerce and retail operations. In addition, it is empirically grounded with significant work done in coordination with TH management to model the demand and inventory costs. The original goal of our study was oriented toward finding the best location for a U.S. East Coast omnichannel warehouse, with a focus on e-commerce fulfillment and one-day delivery. However, the optimization model we developed is a more general multiple-facility-location model that allows a broad set of analyses. Note that our research uses deterministic e-commerce demand, as do Mahar and Wright (2009), Torabi et al. (2015), and Zhang et al. (2016), while many other omnichannel and network-design models use nondeterministic demand to explore availability and service level issues.

Modeling Market Share

A key component of our study is the model for e-commerce market share that TH will capture in each MSA based on the market size, the service provided (i.e., delivery time), and the presence of TH stores and competitor stores. Because this industry is dominated by privately held retailers that do not share data, we needed to estimate the e-commerce market size for each MSA (i.e., the number of e-commerce orders in each MSA). We accomplished this by combining industry-association data, census data, and internal data from TH sales. USA Hockey, the association that governs amateur hockey in the United States, provided the home addresses of over 600,000 hockey players in the United States, and estimated that the annual revenue for hockey equipment sold in the United States is $600 million and that e-commerce is approximately 20 percent of this total, or $120 million per year. With TH's average e-commerce order size of almost $135, this equates to about 891,000 e-commerce orders per year for the United States. A simple approach would apportion these 891,000 orders to MSAs based on relative populations of hockey players, but TH wanted to use its own sales data to seek other factors that influenced hockey-equipment e-commerce sales.

Working with TH management, we created regression models using several data sources for TH's e-commerce sales in an MSA with independent variables, including the number of hockey players and hockey rinks in the MSA, which USA Hockey supplied, the median income of the MSA (from U.S. census data), the number of TH stores in the MSA, and the number of competitor stores in the MSA. Only two of these variables are statistically significant: median income (p-value $= 0.0046$) and number of hockey players (p-value < 0.0001). (Interestingly, the regression models showed that wealthier MSAs tended to place more e-commerce orders per player, but did not place higher value orders on average.) Therefore, to predict total e-commerce demand in an MSA, not only TH e-commerce, we proportionally allocated the 891,000 e-commerce orders to MSAs based on the product of the number of hockey players and the median income in an MSA.

To incorporate the impact of service level, we used the travel time T_{ij} to MSA i from possible warehouse location j, for each warehouse-MSA pair. After extensive discussions with management, we also included a constant "market share factor," which we denoted F, that moderates the expected demand captured. (See Appendix A for the market share model equation.) In this model, larger values of the travel time (i.e., lower service) and larger values of F decrease the market share. The model also includes two adjustments to the market share to account for a loss of e-commerce market share due to competitor chains in an MSA, and a gain in e-commerce market share due to greater brand presence from having TH stores in an MSA. A variety of functional forms could be used to model the market share decrease with increasing delivery time, and our approach differs slightly from the approach that is often used, which includes an exponential in the denominator, such as delivery time squared (Huff 1966). We use a simpler form because it represents the observed relationship between market share and service, other functional forms were confusing to TH management, and we wanted to use a model that is easily understood to enhance the chances of adoption (Levasseur 2015). However, we also conducted extensive sensitivity analysis by varying the market share factor F to explore its impact on the results.

To model the impact of TH and competitor stores in an MSA, we relied on statistical analysis and extensive discussions with TH management. TH management believes that the presence of competitors' stores (possibly stores from multiple chains) in an MSA decreases TH's e-commerce sales in that MSA. The managers also believe that the presence of one or more TH stores in an MSA increases TH e-commerce sales from greater brand awareness. Thus, they believe there is reverse cannibalism (i.e., increasing e-commerce sales) when TH enters a new market with brick-and-mortar stores. The academic literature shows mixed results with some empirical studies showing cannibalization of sales and other studies showing reverse cannibalization; for example, see Pauwels and Neslin (2015) and Cao and Li (2015).

To assess the impact on e-commerce sales from opening TH stores, we evaluated the monthly e-commerce revenue over a three-year period for six MSAs, beginning when TH opened its first store in that MSA. We examined the revenues from 12 months prior to TH opening its first store in the MSA to 24 months after this store's opening. As a control, we used an MSA (i.e., St. Louis) with TH retail but no store changes over the relevant periods. We developed autoregressive integrated moving average (ARIMA) models for these MSAs to test whether the intervention of opening stores is a significant factor for increasing e-commerce sales. The results show that store openings are statistically significant in two of the six MSAs ($p < 0.01$), a little less strong for a third MSA ($p < 0.063$), and not statistically significant for the other three MSAs, although all six MSAs showed e-commerce growth. As an example, results for the ARIMA model for the Chicago MSA are included in Table B.1 (Appendix B). Although these results offer mixed support for reverse cannibalization, management feels strongly that it is important to model e-commerce shipments reflecting reverse cannibalism of sales when TH enters a new MSA that includes retail stores. Consequently, our market-capture models reflect a percentage addition to e-commerce demand (e.g., 10 percent) due to opening TH stores in a new MSA. Given the positive adjustment to market share for the presence of TH stores, management wanted a similar negative adjustment to market share for the presence of competitor stores. Because some large markets (MSAs) have multiple competitor chains with retail stores, the market share is decreased for each competitor chain with a retail store in the MSA.

The net effect of the market share model (see Appendix A) is that the number of orders captured by TH for an MSA decreases with increasing delivery time and the presence of one or more competitive chains, and increases from opening a TH store in the MSA. The market share factor F controls the sensitivity of the market share to the service level (i.e., delivery time); the values of interest to TH management are in the range $1.5 \leq F \leq 4$. Note that the market shares for each MSA-warehouse location pair are calculated exogenous to the warehouse location-optimization model and used as input values.

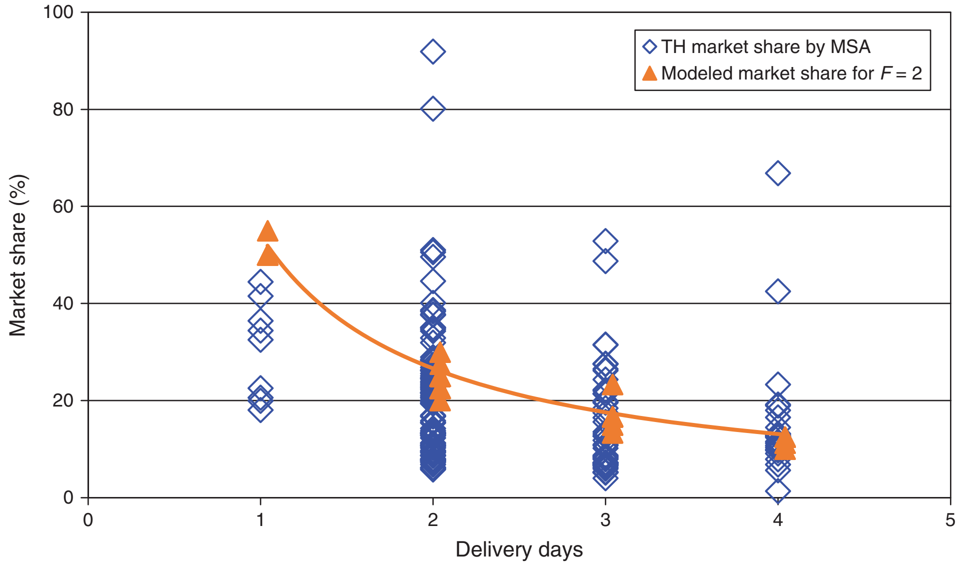
To illustrate the estimation of market capture M_{ij} for one MSA, consider Chicago, a large market where TH has a store presence and two competitor chains have stores. Chicago receives one-day delivery from TH's existing omnichannel warehouse in St. Louis. The median household income in the Chicago MSA is \$70,074 and the MSA has 28,857 hockey players (according to USA Hockey). Over all MSAs in the United States, the sum of the product of median income and number of hockey players is \$37,824,840,861. In Appendix A, we estimate the total e-commerce demand in orders for Chicago as 47,613. Using a 10 percent factor to adjust market shares and a market share factor $F = 2$, we also estimate the Chicago demand captured by TH as 19,045 orders.

Figure 3 shows the fit between the market share model for $F = 2$ for all MSAs that receive more than 70 orders per year; the percentage values from the market share model (Appendix A) for $F = 2$ are shown by solid triangles and are offset slightly to show the underlying estimated market share values (open diamonds). The open diamonds for one, two, three, and four delivery days are the market shares for 177 MSAs, based on TH's actual number of e-commerce orders in each MSA divided by the predicted number of e-commerce orders in each MSA. In MSAs with a small number of orders, the market share estimates can be very large when the actual orders for TH far exceed a small prediction for the total number of orders in an MSA. The market share term in brackets (from the equation for M_{ij} in Appendix A) provides up to six points for each number of delivery days, which correspond to the combinations of having zero, one, or two chain competitor stores (L_i in Appendix A can equal zero, one, or two), and having no or at least one TH store (G_i in Appendix A can equal zero or one) in a particular MSA. The curved line in Figure 3 shows the decline in market share with increasing delivery time. Note the over-prediction of market share for one-day delivery with $F = 2$, which indicates a greater benefit from a larger market share by offering one-day service. Other values of the parameter F provide differing predications; therefore, setting F considering the available data and management expectations is important.

Modeling Warehouse and Inventory Costs

Accurately modeling costs for potential warehouses is important because these costs comprise a large share of the total costs. Costs to open and operate a warehouse are based on the facility capacity and the local real estate and labor-cost rates in the MSA. They demonstrate economies of scale with larger facilities having lower unit costs. We model five possible sizes

Figure 3. (Color online) The Model's Calculated Market Share for $F = 2$ and TH's Market Share vs. the Delivery Days to Each MSA



for warehouses, with each size based on the capacity of orders per year that can be shipped out of the facility. Calculating the inventory investment required for e-commerce fulfillment from each potential warehouse required additional steps. By evaluating TH's current e-commerce demand, we estimated the number of SKUs required for each size of facility. For example, the smallest facility with a capacity of 25,000 annual orders could be expected to ship (and therefore stock) approximately 16,000 unique SKUs. A large fulfillment center like the current facility in St. Louis, which processed 92,000 e-commerce orders in 2014, shipped 31,975 unique SKUs. Additional SKU levels required by facility capacity were built around TH's annual e-commerce demand pattern by SKU. These levels are shown in column 2 of Table 1.

We calculated inventory investment levels for each warehouse size using Optimal Velocity's Inventory Optimizer™ demand forecast and inventory safety stock optimization model (Optimal Velocity 2015), using the actual TH demand and cost data. The demand forecast model in Inventory Optimizer uses five exponential smoothing algorithms whose coefficients are optimized. The forecast program then chooses the model that is most accurate for the preceding 12 months and uses its future prediction of demand in TH's planning process. The forecast error, calculated as the square root of the mean squared error, is used in the safety stock calculation, replacing standard deviation of demand, to represent the nonstationary nature of the demand of most of TH's SKUs (Neale and Willems 2009). Safety stock is optimized using a mixed-integer linear programming (MILP) model in Inventory Optimizer, which allows each SKU to be endogenously assigned its appropriate cycle service level based on item profit, lead time, and the aforementioned forecast error (Millstein et al. 2014). This safety stock optimization maximizes the profit return on inventory investment of the entire inventory set. The inventory investment in column 3 of Table 1 is the average monthly forecast over 12 months divided by two, plus average safety stock.

Table 1. The Inventory Investment for the Five Warehouse Sizes Reflects the Economies of Scale

Warehouse capacity (shipments per year)	Approximate no. of SKUs required	Estimated inventory investment ($)
25,000	16,000	4,109,812
50,000	25,000	5,411,028
75,000	28,500	5,848,257
100,000	32,000	6,098,081
250,000	32,000	7,378,678

The inventory levels and costs in Table 1 demonstrate economies of scale with the inventory investment per unit of capacity falling from $164 for a 25,000-shipment warehouse to about $30 for a 250,000-shipment warehouse. The dramatic decline in inventory investment per unit as warehouse size increases results from the very erratic demand pattern of many of TH's SKUs. With larger warehouses, the aggregation of demand reduces demand variation and improves the forecasts of lower-volume SKUs.

The data in Table 1 reflect warehouses that operate at levels near their capacity. To assess this modeling approach, we measured the warehouse capacity utilization of the optimal networks (from solving the location optimization model) for multiple values of F (F = 1.5, 2, 2.5, 3, 3.5, and 4). Capacity utilization across all warehouses in the optimal solutions ranged between 91 and 100 percent, thereby validating our approach.

An important adjustment to the inventory investment in the warehouse is made (for some MSAs) to reflect the possibility of inventory pooling with the local retail stores. Because TH's omnichannel strategy uses inventory at retail stores in the same MSA as a warehouse for e-commerce fulfillment, we treat the entire MSA (stores plus warehouse) as one inventory location for e-commerce orders. This allows us to decrease the size of the warehouse to reflect inventories in all TH stores in that MSA. In addition, using store inventory for e-commerce orders allows TH to have more attractive stores with larger inventories than retail-only store traffic merits. Thus, TH's omnichannel strategy of making retail store inventory visible to online customers allows stores to stock some lower-volume SKUs, which would not normally justify retail space, so both online and in-store customers can purchase them. Placing lower-volume SKUs in stores goes against conventional wisdom that places only higher-volume SKUs in stores and allocates lower volume SKUs to warehouses. However, for TH, this has provided an unexpected revenue upside.

The consequence of this inventory pooling is that locating a warehouse in an MSA with many TH retail stores requires less warehouse inventory than a warehouse that serves the same demand in an MSA with fewer (or no) TH retail stores requires. Note that our modeling differs from a totally decentralized fulfillment channel where all stores can provide e-commerce fulfillment (Bendoly et al. 2007); we allow e-commerce demands to be filled from retail stores only in MSAs that house a warehouse, and where vehicular traffic conditions allow store inventory to arrive back in the warehouse each day in time for shipping out in the evening. Thus, in congested markets, such as Washington, DC, New York, Los Angeles, and Boston, heavy vehicle traffic does not allow inventory from the retail stores to be transshipped through the warehouse and shipped out the same day; therefore, we did not decrease warehouse inventory in these MSAs to reflect the retail stores' inventory in the MSA. Thus, a variety of practical issues (e.g., the need to maximize retail space in expensive markets, a low number of items per order on average, traffic congestion, and packing and shipping efficiencies at a warehouse) drove TH to prefer shipping e-commerce orders from a warehouse, but to also use store inventories, whenever possible.

The ability to use store inventory to fulfill e-commerce orders in an MSA with an omnichannel warehouse has several benefits and costs. One benefit for stores in an MSA with a warehouse is the increase in store inventory, which might lead to higher in-store sales. Another benefit for these stores relates to differing practices for receiving shipments from vendors. In an MSA with a warehouse, the warehouse receives vendor shipments in large trucks, sorts the inventory by store, and sends it on a small delivery truck on a peddling route to the stores. The small delivery trucks allow safer and more efficient receiving of inventory at the stores. The delivery trucks can also collect items to fill e-commerce orders, which they transport back to the warehouse. In contrast, for stores not in an MSA with a warehouse, vendor shipments are received at stores directly from truck trailers at dock height, which requires items to be handed off from the back of the truck to store employees at ground level. Time studies demonstrated that this practice is less efficient than receiving inventory from the small delivery trucks. In addition, safety incidents have occurred while unloading from the dock-height truck trailers at stores.

The added costs from TH's use of store inventory for e-commerce fulfillment include store labor to pick e-commerce orders in a store (stores are not set up for efficient picking), the additional inventory carried in the store, and a portion of the cost of the peddle truck and driver (note that they are already being used for replenishment of the retail stores). While detailed data are not available on all the benefits and costs of using store inventory for e-commerce fulfillment, TH management believes the net effect in the model should be savings of $10,000 per year for each MSA where store inventory is pooled with the warehouse inventory for e-commerce orders.

Our model also includes costs for warehouse operations to support retail stores with break-bulk functions for the inbound containers and for full-truckload shipments from manufacturers. (Break-bulk includes the activities in a warehouse or depot to unload the large shipments from inbound trailers or containers and then create multiple smaller shipments, generally with a mixture of merchandise, that are sent on to many locations, such as retail stores.) These inbound large shipments are broken down into pallets, which are then sent as less-than-truckload (LTL) shipments to stores. The warehouse operations costs are calculated based on the number of expected LTL shipments to each store per year.

Multiple-Facility-Location Model

To design the omnichannel network, we developed a multiple-facility warehouse-location model that determines (1) the location, number, and size of warehouses to support e-commerce and retail stores; (2) the assignment of e-commerce orders from each MSA to a warehouse; and (3) the assignment of retail stores to a warehouse, all to maximize profit. Ongoing demand and costs are modeled over a five-year period using a net present value (NPV) function and TH's hurdle rate. (Hurdle rate is the minimum rate of return that a company requires to invest in a project and is used in the NPV calculation to discount future cash flows.) The five-year NPV function is used to combine the one-time warehouse opening costs with the ongoing annual costs. Store locations are modeled based on TH's intended 2020 store network of 86 stores.

The profit objective includes a positive contribution based on the average gross profit per order. Transportation costs are included for e-commerce deliveries and for support of retail stores. E-commerce shipping costs for each MSA are calculated using parcel shipping costs from the assigned warehouse. Store-support shipping costs are calculated as the average annual number of pallets shipped to each store multiplied by the LTL pallet shipment costs from the assigned warehouse. Warehouse costs are included in the objective for opening warehouses, operating warehouses, and holding inventory. Use of retail store inventories for e-commerce fulfillment is modeled as a $10,000 annual savings in the baseline case, but we also do a sensitivity analysis that varies this amount down to a $50,000 cost.

Inputs to the multiple-facility-location model include the 23 possible fulfillment-center locations, the 359 U.S. MSAs as demand points, TH and chain competitor store locations, average gross profit per order, NPV hurdle rate, parcel-delivery costs for an average order, parcel-delivery times for all warehouse-MSA pairs, LTL delivery costs (per pallet) for all warehouse-store pairs, and the number of pallets per year for store support. The e-commerce market share in annual orders for each MSA-warehouse combination is an input calculated as we describe in Appendix A.

Three sets of binary decision variables are used in the warehouse location optimization model to determine (1) the locations and sizes of warehouses (chosen from the 23 candidate sites), (2) the assignment of the 359 MSAs to the warehouses for e-commerce shipments, and (3) the assignment of the retail stores (located in 20 MSAs) to the warehouses. Figure 2 shows the 23 possible warehouse sites, which include current MSAs served by TH retail stores, future markets that TH plans to populate with retail stores, and a few locations that are popular e-commerce shipping points. Because TH management feels that only larger warehouses can handle the break-bulk operations required for store support, retail stores can be assigned only to warehouses with capacity greater than 125,000 orders per year.

The model was calibrated and validated with TH's management against the current state with a single warehouse at St. Louis. Although the model optimizes profit from e-commerce orders, TH does not break out profit by channel; therefore, we could not validate the model based on profit. However, we did know the number of e-commerce orders TH currently captures in each MSA, which is also an output of the model. Thus, we calibrated the model by selecting the market share factor F that provides the appropriate number of orders for MSAs. We ran the model for values of F between 1.5 and 4.0 with the single St. Louis warehouse and compared TH's actual e-commerce orders to the orders from the model output. Overall, $F = 3$ provides the most accurate results. For example, TH had 15,080 actual orders in Chicago in the 12 months prior to this analysis and the model indicated 15,871 orders for $F = 3$. However, as we discuss in the following section, *Analysis of Solutions*, TH chose to focus on results with $F = 2$, which provides a higher market share, because of management's belief that fast delivery times will become increasingly important.

We developed and solved the binary linear program for warehouse locations (Appendix A) using Solver Premium Platform with the large-scale LP/IP solver. This optimization software was chosen by the modeling team because it uses Microsoft Excel as a foundation, and TH managers are comfortable using Excel. This supports the influence and importance of "active and ongoing interaction between manager and model builder" as noted by Levasseur (2015, p. 364). Building the model in Excel helped enable adoption and increase the potential for ongoing use as conditions change. Model solution times ranged from five minutes to several hours, and were deemed acceptable by TH management for a strategic analysis.

Analysis of Solutions

The market share factor F is an important parameter in the model because it determines the response of market share to the service level (delivery time from the warehouse). Model results for different values of F show how the market share factor impacts the optimal solution; however, the appropriate value for this is uncertain given the unknown actual market shares for this industry and the uncertain e-commerce market size. Further complicating the choice of the market share factor is that TH anticipates the number of retail competitors with e-commerce capability may consolidate from eight to four in a few years.

Given these unknowns, we conducted a sensitivity analysis, varying the parameter F from 1.5 to 4.0, in 0.1 increments. The results shown in Table 2 helped guide the decisions the management team made. Table 2 shows the optimal warehouse locations, the number of orders captured by TH (No. of orders), profit (five-year NPV), and average delivery days for e-commerce shipments for 26 levels of F. As expected, as the market share factor F increases, TH becomes less competitive; therefore, the number of orders and the profit fall dramatically. However, the average level of service (delivery days) varies much less and stays between 1.66 and 2.15 days, because the optimal warehouse locations adjust to reduce delivery times and thereby increase market capture and revenue.

Table 2 reveals some interesting patterns in optimal warehouse locations. Only four locations (of 23 possible MSAs) are selected as warehouses, with Detroit and Minneapolis almost always appearing (25 and 24 times, respectively, out of 26 solutions), albeit with different capacities in some cases. Further, the 26 solutions in Table 2 show only seven different configurations of the four warehouses, and the general trend can be explained as follows:

—With small F (in the range 1.5–2.4), the number of orders captured decreases from 432,000 to 287,000 and three or four warehouses are always used: Philadelphia with capacity 125,000 (except for $F = 1.5$); Minneapolis with capacity 50,000, except for the smallest F values when it has 125,000; Chicago and (or) Detroit, where one has capacity 125,000 and the other has 50,000 or 0;

—With medium F (in the range 2.6–3.3), the number of orders captured decreases from 225,000 to 199,000 and three warehouses are used: Detroit always with capacity 125,000; Minneapolis usually with capacity 50,000; and usually either Chicago with capacity 50,000 or Philadelphia with capacity 25,000.

—With large F (in the range 3.5–4.0), the number of orders captured decreases from 175,000 to 166,000 and the warehouses selected are always Detroit with capacity of 125,000 and Minneapolis with capacity of 50,000.

—The model never locates warehouses in the large markets with heavy vehicular traffic congestion (e.g., Washington DC, New York–New Jersey, Los Angeles, Boston), because the inability to use store inventories effectively increases the inventory required in warehouses, which along with the higher costs of purchasing or leasing warehouse space in these markets ensures that they are never optimal locations.

Table 2 also exhibits some anomalies for certain values of F, such as 2.1, 2.2, and 3.4, where the optimal locations differ substantially from neighboring values of F. These dramatic changes were illogical to TH's management; therefore, we used the model with some warehouse locations fixed open to help management understand these changes; for example, how near-optimal solutions (within 1 percent of the optimal profit) can be found with Minneapolis and (or) Detroit

Table 2. Results of the Sensitivity Analysis for the Market Share Factor *F*

F	Minneapolis	Chicago	Detroit	Philadelphia	No. of orders	Profit ($ millions) ($)	Average no. of delivery days
1.5	125,000	50,000	50,000	250,000	431,967	27.146	1.66
1.6	125,000	X	125,000	125,000	374,881	25.078	1.86
1.7	125,000	X	125,000	125,000	367,829	23.985	1.78
1.8	50,000	125,000	50,000	125,000	350,000	22.338	1.81
1.9	50,000	125,000	50,000	125,000	343,971	21.529	1.80
2.0	50,000	125,000	50,000	125,000	332,460	20.043	1.77
2.1	X	125,000	50,000	125,000	300,000	18.928	1.89
2.2	50,000	125,000	X	125,000	299,956	18.450	1.74
2.3	50,000	X	125,000	125,000	294,915	17.613	1.72
2.4	50,000	X	125,000	125,000	287,215	16.609	1.70
2.5	50,000	50,000	125,000	25,000	245,469	15.549	2.03
2.6	50,000	50,000	125,000	X	225,000	15.366	2.17
2.7	50,000	50,000	125,000	X	221,659	14.896	2.10
2.8	50,000	50,000	125,000	X	215,844	14.146	2.10
2.9	50,000	50,000	125,000	X	210,430	13.446	2.10
3.0	75,000	X	125,000	X	200,000	12.967	2.19
3.1	50,000	X	125,000	25,000	199,893	12.612	2.14
3.2	50,000	X	125,000	25,000	200,000	12.610	2.11
3.3	50,000	X	125,000	25,000	198,614	12.404	2.06
3.4	X	50,000	125,000	X	175,000	11.966	2.24
3.5	50,000	X	125,000	X	175,000	11.827	2.25
3.6	50,000	X	125,000	X	175,000	11.811	2.21
3.7	50,000	X	125,000	X	174,545	11.727	2.15
3.8	50,000	X	125,000	X	171,500	11.332	2.15
3.9	50,000	X	125,000	X	168,612	10.956	2.15
4.0	50,000	X	125,000	X	165,868	10.599	2.15

Note. X represents a location not selected by the model.

forced open, but how profit optimization can sometimes produce a cascade of changes (e.g., when forcing Minneapolis open results in closing Chicago and opening a small warehouse in Denver).

Table 3 provides cost details for three solutions in Table 2 that correspond to $F = 2, 3$, and 4 to show how individual cost components vary with the market share factor, because that causes the number of orders, warehouse locations, and warehouse sizes to change (Table 2). The changes in costs in Table 3 show the nonlinear response to the number of orders captured (and *F*). For example, the last two rows of Table 3 show that as *F* increases from 2 to 3 to 4, the inventory holding cost per order decreases from $0.409 to $0.328, while the e-commerce delivery cost per order increases from $0.323 to $0.351. Note that these total costs are based on the actual unit costs, which vary considerably across the warehouse locations, and result from the differing optimal shipment patterns.

In summary, the results and sensitivity analysis demonstrate that an optimal or near-optimal network for TH can be produced from the same set of four warehouses over a broad range of market share factors, and that two key locations appear to be Detroit and Minneapolis. Detroit is a consistently optimal choice for a large e-commerce fulfillment warehouse (125,000

Table 3. Results for Orders, Locations, and Cost Components Vary Considerably with Changes in the Market Share Factor *F*

	$F = 2$	$F = 3$	$F = 4$
No. of orders	332,460	200,000	165,868
Locations	Min, Chi, Det, Phil	Min, Det	Min, Det
Five-year NPV inventory holding cost ($1,000) ($)	14,921	7,265	5,800
Five-year NPV e-commerce delivery cost ($1,000) ($)	11,798	7,439	6,196
Five-year NPV facility operating cost ($1,000) ($)	7,892	4,448	3,833
Five-year NPV store support delivery cost ($1,000) ($)	1,558	1,643	1,643
Warehouse opening cost ($1,000) ($)	349	228	199
Total cost ($1,000) ($)	36,518	21,024	17,671
Inventory holding cost per order ($)	0.409	0.346	0.328
E-commerce delivery cost per order ($)	0.323	0.354	0.351

orders), except with smaller values of F when TH can capture enough e-commerce orders from the large (and competitive) Northeastern market by opening a large warehouse in Philadelphia. Minneapolis is usually also an optimal location, although with a smaller capacity (usually 50,000) than Detroit. Minneapolis is valued because it is a very large market that has low levels of competition (in part due to the very strong retail position of TH and one of its competitors in this market). The Minneapolis warehouse also serves customers in Alaska, which is a relatively large market with no retail chains.

The data collected for this study showed that MSAs with a large number of TH retail stores generally have enough inventory in the stores to handle up to about 50,000 e-commerce orders per year. If such an MSA had a warehouse and the store inventory could be delivered back to the warehouse before the parcel-shipping company pick-up time at the end of the day, then the store inventory could be used to fulfill e-commerce orders. Results show that optimal warehouse locations gravitate to MSAs with large numbers of retail stores to take advantage of this store inventory and thereby allow a smaller, lower-cost warehouse. To further explore the role of pooling store inventory with the warehouse inventory in the same MSA, we conducted additional analyses, which we summarize in Table 4. The first two rows of results in Table 4 show solutions that do not allow use of store inventories with fixed warehouse locations in St. Louis only (the current warehouse), and with St. Louis plus a new warehouse in Philadelphia (the location originally thought useful to handle Northeastern demand). Adding Philadelphia improves service; however, both designs produce a net loss (i.e., negative profit). The next row of Table 4 shows that the optimal solution without using any store inventories for e-commerce fulfillment is a single warehouse in Detroit, which provides a small NPV profit. A much better solution is achieved by allowing e-commerce fulfillment from store inventories, in which case the optimal solution, shown in the last row of the table, has four warehouses with a $20 million NPV profit, along with a high service level. These results illustrate how the decision to use store inventories can have a dramatic effect on both profit and the optimal locations of omnichannel warehouses.

Table 4. Allowing the Use of Retail Store Inventories for E-Commerce Fulfillment Is Shown to Be Beneficial

Use of store inventory	Warehouse locations	NPV profit ($\$ \times 1{,}000$) ($)	Service (average days)
No	St. Louis*	−2,226	2.58
No	St. Louis*, Philadelphia*	−9,144	2.12
No	Detroit	1,907	2.31
Yes	Detroit, Minneapolis, Chicago, Philadelphia	20,043	1.77

Notes. A fixed warehouse location is indicated by "*"; other locations are optimal solutions from the model. Results are for market share factor $F = 2$.

An alternative to locating new warehouses to improve service and increase one-day delivery is to use next-day-air shipping services. TH shipments are very often odd-shaped items (e.g., hockey sticks) and the average cost premium for next-day air to all MSAs from the St. Louis warehouse is about $20 per shipment. To assess the alternative of using next-day air, we compare the service for the current network with a single warehouse in St. Louis (using $F = 2$) with that for the optimal (profit-maximizing) network. There are 135,535 orders that require more than one-day delivery in the current network, but receive one-day delivery in the optimal network. To use only the current single warehouse in St. Louis and ship the 135,535 orders next-day air adds about $2.7 million to the transportation costs, but allows savings compared to the optimal network (with multiple warehouses) in warehouse operating and inventory costs. The net impact is that to match the service level from the optimal network, using only a St. Louis warehouse with next-day-air shipping, will decrease the profit by $1.4 million.

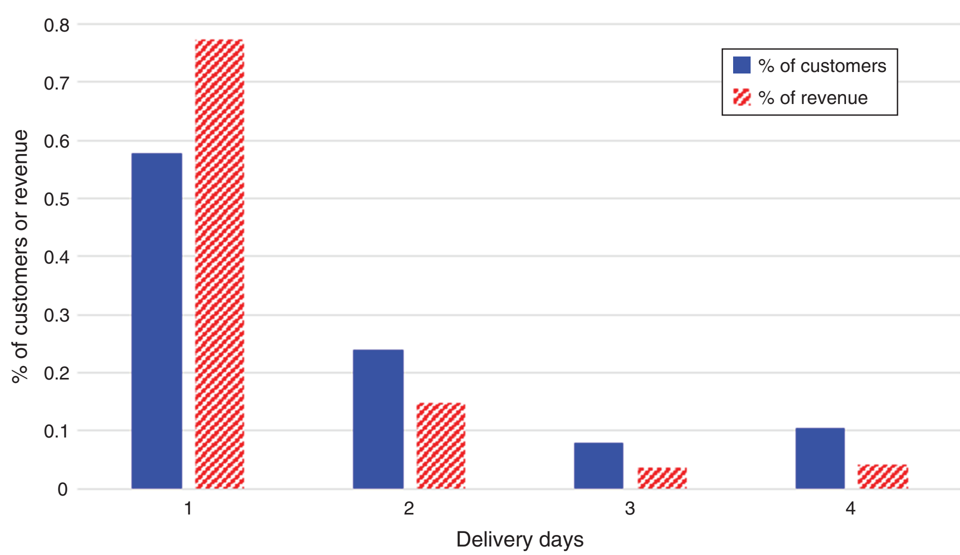
Management Decision and Implementation

The results of our study show that maintaining the St. Louis warehouse and adding one warehouse in Philadelphia is not an optimal solution. Following analyses and experimentation with the location model, TH's management team decided to put a 50,000-order-per-year warehouse in Minneapolis, a 125,000-order-per-year warehouse in Chicago, a 50,000-order-per-year warehouse in Detroit, and a 125,000-order-per-year warehouse in Philadelphia. This decision follows the model's general recommendations with lower values of the market share factor F; however, TH put the larger facility in Chicago rather than Detroit. Reasons for this include the proximity of Chicago to the current headquarters in St. Louis and quality-of-life considerations for the operations management team, which would have to relocate from headquarters to the new warehouse location. (The warehouse operations director and his supervisors have long tenure with TH, and management thought that hiring new managers in a new location would be unacceptably disruptive.)

Based on a distribution system with four omnichannel warehouses, using optimal assignments to MSAs and optimal sizes, we calculated the percentage of customers and percentage of revenues that will receive one-, two-, three-, and four-day service (Figure 4). Although the western United States and Alaskan markets are far from the closest e-commerce shipping point, one-day service is provided to 58 percent of USA Hockey members, and these orders generate 77 percent of total e-commerce revenues. An additional 24 percent of customers, who generate 15 percent of revenues, receive two-day service. These results show how the model seeks to give better service to the more valuable markets (i.e., MSAs), not only the markets with more players. (Recall that the e-commerce market size for an MSA depends on the number of hockey players *and* the median income within the MSA.) Note that 92 percent of revenues are from customers receiving one- or two-day service, which is a result of locating warehouses near the major markets in the upper Midwest and Northeast. These results are important to TH, and the company plans to advertise that its network will reach about 60 percent of its customers in one day. This contrasts with TH's large competitors (one of which has its warehouse in Dallas and another close to Boston) whose networks cannot match TH's speed of delivery across the United States.

To further improve service, TH has been considering allowing e-commerce fulfillment from small warehouses in Denver and St. Louis. This is motivated partly by the recent acquisition of a competitor with a small warehouse that supported its Denver stores and e-commerce operations. The small warehouse in St. Louis is driven by the need for inventory-supporting customer service and marketing operations at headquarters. The management team asked us to evaluate a configuration with four main omnichannel warehouses (i.e., Minneapolis, Chicago, Detroit, Philadelphia), along with small store-based e-commerce fulfillment centers in Denver (10,000 orders per year) and St. Louis (5,000 orders per year). The result is a revenue increase of $533,000 per year from the improved level of service, because one-day service increased by 1 percent (5,698 more customers) and two-day service increased by 2 percent (14,048 more customers). However, the added inventory costs are over $1.080 million in the two store-based e-commerce fulfillment centers, due partly

Figure 4. (Color online) This Graph Shows the Percentage of Hockey Players Served, and the Percentage of Revenue Provided by One-, Two-, Three-, and Four-Day Service from the Network Selected by TH



to the absence of inventory economies of scale in these smaller facilities.

Conclusions

Implementing omnichannel distribution can be challenging and little applied research is available to support optimal designs and implementation. This study seeks to contribute in this area, although we do not intend to provide comprehensive solution methods for all omnichannel distribution systems. TH, and the specialty sporting goods market in general, have few stores relative to many industries, and the market is well defined, with the locations of a very high percentage of customers known. Still, there are several general lessons to take away from this study.

—Optimal omnichannel warehouse locations depend on the level of e-commerce demand and on economies of scale in inventory and operating costs. About 30 percent of TH's demand is via e-commerce; therefore, our results are in line with the theoretical findings from Bendoly et al. (2007), which favor the use of decentralized channels (e.g., store inventories) for lower levels of e-commerce demand. The models also show how warehousing economies of scale can overcome the benefits of having many small e-commerce warehouses to achieve high service levels (an aspect that TH management considered originally).

—Network design depends on the fulfillment strategy regarding the use of inventory from retail stores. The ability to leverage in-store inventory for e-commerce sales can be economically beneficial and can improve service levels, a benefit that will be especially important with the growing trend toward fast delivery (i.e., one day or less).

—Sensitivity analysis with a comprehensive distribution-system design model can help clarify trade-offs and identify key parameters, especially in the face of uncertainty and in competitive environments where market capture and competitor responses are uncertain.

—Although many e-commerce omnichannel strategies include shipping orders from the backrooms of individual stores at the beginning, if orders contain more than one item, the probability of having the right inventory in any one store can be very low. Where practical, bringing items from retail stores back to an omnichannel warehouse can be beneficial.

Our research shows how optimization modeling, which includes practical details of real-world operations that incorporate management concerns and beliefs in an uncertain and competitive business environment, complements more theoretical modeling to shed light on challenging supply chain design issues. This illustrates the value of combining the power of optimization with managerial decision making and strategic planning in the face of future uncertainty.

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Appendix A

The omnichannel warehouse network design model is formulated as a capacitated fixed-charge location problem, where each warehouse location has multiple possible capacities. The formulation uses four sets: I for the set of markets, J for the set of possible warehouse locations, S for the set of cities with TH stores, and K for the set of warehouse sizes.

The formulation includes the following parameters:

p = gross profit per order for TH;
v = TH's hurdle rate;
γ_j^k = capacity in orders for a warehouse of size k at location j;
M_{ij} = e-commerce demand in orders per year from MSA i that will be captured if assigned to a facility at location j;
h_j^k = annual inventory holding costs for a warehouse of size k at location j;
a_j^k = annual operating costs for a warehouse of size k at location j;
f_j^k = one-time fixed costs to open a warehouse of size k at location j;
c_{ij} = parcel shipping cost for the average order ($ per order) to MSA i from a warehouse at location j;
d_{sj} = LTL shipping cost ($ per pallet) to MSA s from a warehouse at j;
b_s = number of pallets shipped to all TH stores in MSA s;
e_j^k = labor cost savings per TH store from having a warehouse of size k at location j; and
q_j = number of TH retail stores in proximity to a warehouse at location j.

The formulation uses three sets of binary variables for the locations of warehouses of appropriate size and the allocation of both MSAs and retail stores to a warehouse:

$Y_{ij} = 1$ if MSA i is served by a facility at location j;
$X_j^k = 1$ if a facility of size k is open at location j, $k = \{1, 2, 3, 4, 5\}$;
$Z_{sj} = 1$ if stores in MSA s are served by a facility at location j;

To calculate the market share M_{ij}, we first estimate the e-commerce demand in annual orders for MSA i, O_i, by apportioning the total of 891,000 orders in the United States to the MSAs:

$$O_i = 891{,}000 \cdot \frac{\textit{no. of hockey players in MSA } i \times \textit{median income of MSA } i}{\sum_i \textit{no. of hockey players in MSA } i \times \textit{median income of MSA } i}.$$

In the example using Chicago, as we discuss in the *Modeling Market Share* section, we can use this equation to estimate the total e-commerce demand in orders for Chicago as:

$$O_{Chicago} = 891{,}000 \frac{28{,}857 \times \$70{,}074}{\$37{,}824{,}840{,}861} = 47{,}613.$$

The model for the market share (in annual orders) captured by TH in MSA i by serving it from warehouse location j that was developed in concert with TH management is given by

$$M_{ij} = O_i \left[\frac{1}{T_{ij} \times F} - \alpha_i \times L_i + \beta_i \times G_i \right].$$

Using the same example, a 10 percent factor for α_i and β_i to adjust market shares, and a market share factor $F = 2$, gives the Chicago demand captured by TH as

$$M_{\textit{Chicago, St. Louis}} = 47{,}613 \left[\frac{1}{1 \times 2} - 0.1 \times 2 + 0.1 \times 1 \right] = 19{,}045 \text{ orders.}$$

The three terms in brackets model the market share (percentage) that TH captures of the total e-commerce demand in MSA i (O_i). Larger values of the travel time (i.e., lower service) and larger values of F decrease the first term. For example, using $F = 2$, the first term in the brackets is $1/(1 \times 2) = 50\%$ if an MSA is served by a TH warehouse in one day, $1/(2 \times 2) = 25\%$ if the MSA is served by a TH warehouse in two days, and $1/(3 \times 2) = 16.7\%$ for three-day service. The second term in brackets captures the decrease in market share due to competitor chains in an MSA. Parameter α_i is the percentage decrease in market share for MSA i for each competitor chain in MSA i and L_i is the number of competitor chains in MSA i. The third term in brackets above captures the increase in market share due to having a TH store in the MSA. Parameter β_i is the percentage increase in market share for MSA i from having one or more TH stores in MSA i, and G_i is a binary variable indicating whether TH has a retail store in MSA i. The parameters α_i and β_i are selected by management based on market conditions. In the results presented, we use $\alpha_i = \beta_i = 10\%$ for all MSAs.

The objective function in the network design model consists of the gross profit minus the relevant costs for warehousing, holding inventory, delivery to stores and to MSAs for e-commerce orders, and the in-store-market labor cost savings. The components of the objective are as follows:

GP = Annual gross profit = $\sum_{i,j} pM_{ij}Y_{ij}$;
FO = Facility opening costs = $\sum_{k,j} f_j^k X_j^k$;
OI = Annual operating + inventory holding costs = $\sum_{k,j}(a_j^k + h_j^k)X_j^k$;
ED = E-commerce delivery costs = $\sum_{i,j} c_{ij}M_{ij}Y_{ij}$;
SS = Store-support delivery costs = $\sum_{s,j} b_s d_{sj} Z_{sj}$;
LC = DC in-store market labor-cost savings = $\sum_{k,j} q_j e_j^k X_j^k$.

The annual net profit can be calculated as $GP + LC - OI - ED - SS$. All components except the facility opening costs are annual costs; therefore, the five-year discounted net profit is given by

$$\sum_{i,j} A_{ij}Y_{ij} + \sum_{k,j} B_{jk}X_j^k - \sum_{s,j} C_{sj}Z_{sj},$$

where

$$A_{ij} = (p - c_{ij})M_{ij} \times \sum_{t=1}^{5} \frac{1}{(1+v)^t};$$

$$B_{jk} = [q_j e_j^k - (a_j^k + h_j^k)] \times \left[\sum_{t=1}^{5} \frac{1}{(1+v)^t} \right] - f_j^k;$$

$$C_{sj} = b_s d_{sj} \times \sum_{t=1}^{5} \frac{1}{(1+v)^t}.$$

The term A_{ij} includes the gross profit (GP) and e-commerce delivery costs (ED), B_{jk} includes the facility opening costs (FO), warehouse operating and inventory holding costs (OI), and the DC in-store market labor-cost savings (LC), and C_{sj} includes the store-support delivery costs (SS).

The omnichannel location model can then be formulated as

$$\max \sum_{i,j} A_{ij}Y_{ij} + \sum_{k,j} B_{jk}X_j^k - \sum_{s,j} C_{sj}Z_{sj} \tag{A.1}$$

$$\text{subject to} \sum_j Y_{ij} = 1, \quad \forall i; \tag{A.2}$$

$$Y_{ij} \le \sum_k X_j^k, \quad \forall i, j; \tag{A.3}$$

$$\sum_j Z_{sj} = 1, \quad \forall s; \tag{A.4}$$

$$Z_{sj} \le X_j^4 + X_j^5, \quad \forall s, j; \tag{A.5}$$

$$\sum_i M_{ij}Y_{ij} \le \sum_k \gamma_j^k X_j^k, \quad \forall j; \tag{A.6}$$

$$\sum_k X_j^k \le 1, \quad \forall j; \tag{A.7}$$

$$Y_{ij} \in \{0,1\}, \quad \forall i, j; \tag{A.8}$$

$$X_j^k \in \{0,1\}, \quad \forall j, k; \tag{A.9}$$

$$Z_{sj} \in \{0,1\}. \quad \forall s, j. \tag{A.10}$$

The objective (A.1) maximizes the five-year NPV of net profit. The constraints are those from a capacitated fixed-charge location problem. Constraint (A.2) ensures each MSA is served by one warehouse. Constraint (A.3) ensures MSAs are assigned only to open facilities. Constraint (A.4) ensures each TH retail store is served by one warehouse. Constraint (A.5) ensures TH retail stores are assigned only to warehouses of the two largest sizes. Constraint (A.6) ensures the capacity of a warehouse is large enough for the assigned e-commerce demand. Constraint (A.7) ensures a warehouse is opened at only one size level. Constraints (A.8)–(A.10) are domain constraints.

Appendix B

Table B.1. Summary Fit Statistics and Coefficient Estimates of the ARIMA Intervention Model for Chicago

Model statistics					
	Model fit statistics	Ljung-Box Q(18)			
No. of predictors	Stationary R-squared	Statistics	DF	Sig.	No. of outliers
1	0.938	21.006	18	0.279	7

ARIMA model parameters						
			Estimate	SE	t	Sig.
Sales	Constant		2,404	373.2	6.442	0.000
Stores	Numerator	Lag 0	8,687	1,348	6.444	0.000

Outliers						
			Estimate	SE	t	Sig.
August 2006	Transient	Magnitude	4,801	1872	2.564	0.012
		Decay factor	0.907	0.092	9.880	0.000
Dec 2007	Additive		11,267	2,705	4.166	0.000
Dec 2008	Additive		24,316	2,733	8.898	0.000
Jan 2009	Transient	Magnitude	11,547	2,356	4.902	0.000
		Decay factor	0.747	0.088	8.461	0.000
Aug 2009	Transient	Magnitude	13,494	2,078	6.493	0.000
Dec 2009	Additive		34,360	3,021	11.375	0.000
Jan 2010	Additive		8,966	3,239	2.768	0.007

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Verification Letter

Rob Bowers, Vice President of Strategy, Total Hockey, 3120 Riverport Tech Center Drive, Maryland Heights, MO 63043, writes:

"Total Hockey is a 17-year-old retailer specializing in hockey and lacrosse equipment and apparel needs for amateur participants. Total Hockey has long been an organization driven by data and innovation, from the market analysis that drives store site selection, to the demographic data from our partnership with USA Hockey, to our marketing strategies built around personas identified through our 12-year-old loyalty program.

"Almost four years ago, as Total Hockey's footprint was growing from three MSA's in the upper Midwest to seven MSA's stretching from St. Louis to Philadelphia and our ecommerce business was continuing its rapid growth as a

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central element of our omnichannel strategy, it became clear that we needed to enhance our capabilities in inventory management, logistics, and process management.

"In 2015, we began working with Dr. Mitch Millstein to optimize our facility locations supporting e-commerce and in-store inventory needs. From this work we developed a new omnichannel warehousing and inventory plan that entirely redefined our approach to warehousing, inventory management, store distribution and fulfillment. The modeling efforts caused us to rethink our expansion strategy from needing a single new east-coast warehouse to a more complex distribution system with multiple warehouses as well as e-commerce fulfillment from retail stores. This work illuminated some options we had never considered, including the value of in-store inventories to support e-commerce sales. As a result of the analyses by Dr. Millstein we have begun the move to an improved omnichannel design by reassigning MSAs to new warehouses, greater leveraging of in-store inventories to satisfy e-commerce demands, and exploring acquisitions of new warehousing space in serval strategic locations. We have already seen an improvement of more than $300,000 from both more efficient shipping strategies and better inventory management."

Mitchell A. Millstein is the associate director of the University of Missouri—St. Louis' College of Business Center for Business and Industrial Studies, and a faculty member in the Supply Chain and Analytics Department. Prior to joining the College of Business he worked 19 years as a Lean and Supply Chain Consultant, working with over 120 companies. He is the founder or co-founder of three companies include Supply Velocity (consulting), Andrea's Gluten Free (food production), and Optimal Velocity (software). His research interests include applied optimization modeling, manufacturing work-flow methods and supply chain performance measures. He earned his PhD in logistics and supply chain management at the University of Missouri—St. Louis, has a MBA from Washington University and an engineering degree from Rutgers University.

James F. Campbell is professor of supply chain and analytics at University of Missouri—St. Louis. He holds an MS and PhD in industrial engineering and operations research from the University of California, Berkeley. His main research interests are in modeling and optimization of logistics systems, including hub location and hub network design, drone delivery systems, facility location modeling, and use of continuous approximation modeling.