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An Inquiry into Supply Chain Strategy Implications of the Sharing Economy for Last Mile Logistics

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An Inquiry into Supply Chain Strategy Implications of the Sharing Economy for Last Mile Logistics

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DEDICATION

To my beautiful fiancée, Lauren, for your support, patience, and encouragement throughout this process.

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ABSTRACT

As the prevalence of e-commerce and subsequent importance of effective and efficient omnichannel logistics strategies continues to rise, retail firms are exploring the viability of sourcing logistics capabilities from the sharing economy. Questions arise such as, “how can crowdbased logistics solutions such as crowdsourced logistics (CSL), crowdshipping, and pickup point networks (PPN) be leveraged to increase performance?” In this dissertation, empirical and analytical research is conducted that increases understanding of how firms can leverage the sharing economy to increase logistics and supply chain performance. Essay 1 explores crowdsourced logistics (CSL) by employing a stochastic discrete event simulation set in New York City in which a retail firm sources drivers from the crowd to perform same day deliveries under dynamic market conditions. Essay 2 employs a design science paradigm to develop a typology of crowdbased logistics strategies using two qualitative methodologies: web content analysis and Delphi surveys. A service-dominant logic theoretical perspective guides this essay and explains how firms co-create value with the crowd and consumer markets while presenting a generic design for integrating crowdbased models into logistics strategy. In Essay 3, a crowdsourced logistics strategy for home delivery is modeled in an empirically grounded simulation optimization to explore the logistics cost and responsiveness implications of sharing economy solutions on omnichannel fulfillment strategies.

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I. INTRODUCTION

Consumer preference for online shopping continues to grow worldwide. In 2017, the global e-commerce market amounted to about $2.3 billion (see Figure 1 in Appendix) and is projected to nearly double by 2021 (eMarketer 2018). Much of this growth is projected to occur in the Southeast Asia, North America, and the European Union, but globally, e-commerce is on the rise.

In the United States, 2017 saw e-commerce grow at a year-over-year (YOY) rate of 16.9% while total retail sales grew at 4.8% (U.S. Census Bureau 2018). The trend of e-commerce sales growing faster than total retail sales has been occurring for at least a decade and implies that online shopping will continue to comprise an ever-larger part of the retail sector. This underscores the importance developing effective and efficient logistics and supply chain management strategies to support the growing online shopping sector.

To deal with changing consumer preferences and to develop more effective/efficient logistics capabilities, many retailers have transitioned from multichannel to omnichannel strategies (Bell et al. 2014; Hübner et al. 2016; Ishfaq et al. 2016). Omnichannel supply chains are an evolution of multichannel distribution strategies where logistics managers are expected to be able to fill orders received on a multitude of platforms, including mobile phones, websites, call centers, kiosks, or storefronts, from any inventory holding location. This means that in an omnichannel strategy, logistics managers have to view their inventory as a single mass of goods, rather than existing in distinct channels with little to no crossover. In a multichannel strategy, an online order might only be filled from a single e-commerce distribution center, but in an omnichannel strategy, that same order would be filled from the nearest or most logical location, which could be a full-service distribution center or even a retail storefront.

The novel omnichannel approach creates new challenges. For example, the last mile to the end customer now potentially exists in all channels, not just the direct-to-consumer channel as it would in a multichannel strategy. Last mile deliveries can be far more complex due to the individual differences between customer locations. For instance, a driver making multiple deliveries on a single route may have a customer in an apartment complex behind a locked gate and another asking for special drop off instructions. The volume of these challenges increases in an omnichannel strategy since the last mile resides in potentially all channels, which means that the ability to develop an effective and efficient last mile delivery strategy is now more important than ever.

To deal with this challenge, companies are exploring disruptive technologies, including drones and autonomous vehicles (Kunze 2016; Savelsbergh and Van Woensel 2016). Others are turning to the sharing economy for scalable "crowdbased" solutions. One such crowdbased solution is Crowdsourced Logistics (CSL), more commonly thought of as the "Über-for-logistics" business model, which is beginning to gain legitimacy as a mode of last mile transportation. CSL refers to a shipper's procurement of logistics services through a mobile or computer application from members of the crowd who provide those services as an independent contractor using a personally owned vehicle asset. Amazon Flex is the online retail giant's venture into CSL, which has expanded from its pilot tests in two cities to being a staple of its logistics strategy in over thirty US cities. UPS has invested in Deliv, a CSL startup, to explore the business model for same day delivery. There are other CSL startups as well such as Instacart, in which drivers shop for and deliver groceries to customers, and Postmates, where customers order food from restaurants that is delivered via CSL drivers.

While these examples are mostly relevant to the last mile of the supply chain, other sharing economy-inspired or "crowdbased business models" have also been innovated for upstream operations as well. For example, Flexe is a technology platform that allows for companies to share access to underutilized warehouse storage capacity and management services. Much like Airbnb where a home owner shares access to privately-owned property to increase utilization rates, Flexe has created a network of warehouses where organizations in need of storage space can find it quickly without having to invest in long term contracts or make large capital investments.

As innovative crowdbased business models become more prevalent in logistics and supply chain management, important questions arise, such as, "how can crowdbased logistics solutions such as crowdsourced logistics (CSL) or B2B asset sharing be leveraged to increase performance?" In this dissertation, empirical and analytical research is conducted in three essays that increase understanding of how firms can leverage this class of crowdbased logistics business models to increase logistics and supply chain performance.

Essay 1 explores crowdsourced logistics (CSL) by employing a stochastic discrete event simulation set in New York City in which a retail firm sources drivers from the crowd to perform same day deliveries under dynamic market conditions. Using a contingency theory lens (Van de Ven et al. 2013), Essay 1 contributes a nascent understanding of how CSL performs in terms of logistics effectiveness by simulating same-day delivery services from a distribution center to 1,000 customer locations throughout New York City under dynamic market conditions and by comparing the results to those of a traditional dedicated fleet of delivery drivers. The results show that while CSL presents an enticing source of low cost delivery capacity, logistics effectiveness metrics can be lower than they would under a dedicated fleet of drivers when demand is at average levels. However, when demand surges unexpectedly beyond capacity of dedicated fleets, CSL may be a means of quickly expanding delivery capacity, albeit with a lower service level. These findings suggest the prospect of a hybrid fleet of dedicated and crowdsourced drivers and implies a novel fleet sizing and fleet mix problem.

Essay 2 inductively explores the broader class of Crowdbased Logistics Business Models (CLBMs), to which CSL and B2B Asset Sharing belong. A design science paradigm (van Aken et al. 2016) is employed to develop a typology of crowdbased logistics strategies using two qualitative methodologies: web content analysis and Delphi panels. A service-dominant logic theoretical perspective guides this essay (Vargo and Lusch 2004; Lusch 2011) and explains how firms co-create value with the crowd and consumer markets while presenting a generic design for integrating crowdbased models into logistics strategy. Experienced logistics managers and executives were also asked how they expect certain task environment variables to affect the value co-creation process in CLBMs. Consensus among the experts was achieved that geographical regions, time urgency of deliveries, and product characteristics were all important factors to consider in designing and implementing CLBMs.

Essay 3 ties findings from the first two essays together to accomplish two objectives from a systems level perspective (Von Bertalanffy 1972): 1) understand how hybrid delivery fleets comprised of dedicated and crowdsourced delivery are designed in terms of fleet size and mix based on logistics strategy and task environment variables; and 2) examine the expected impact of CSL on financial and operational performance in an omnichannel network in terms of the cost-service tradeoff. To accomplish these goals, a multimethod (agent-based and discrete event) simulation optimization model is developed, and insight is provided to explore the cost and responsiveness tradeoff of CSL. The results of Essay 3 show that CSL is a more profitable source of last mile delivery capacity, but its attractiveness is hindered by lower logistics customer service quality, as shown in Essay 1. This essay also shows that the optimal hybrid fleet size and mix depend heavily on the costs for each driver type and crowdsourced driver delivery acceptance rates. This essay also suggests that the most beneficial application of a hybrid fleet of delivery drivers is same day delivery of functional products under a Ship from Store omnichannel fulfillment policy.

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Appendix – Figures

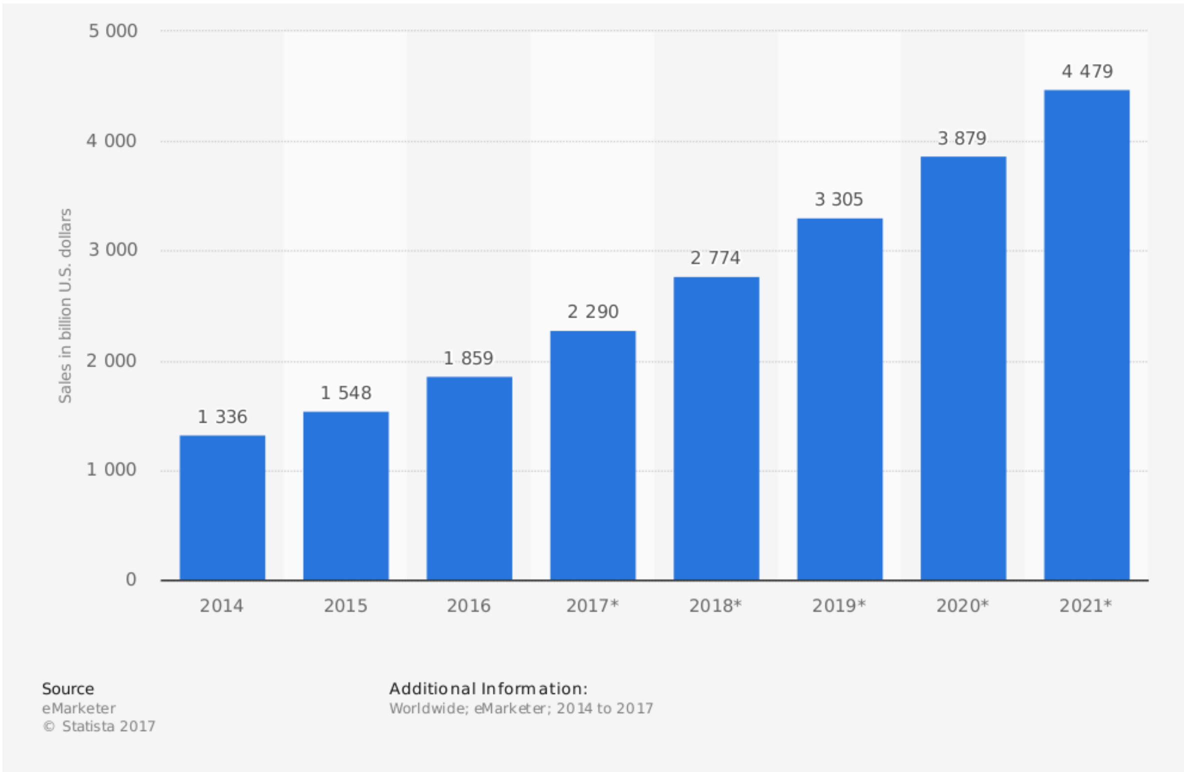

Figure 1 - Retail e-commerce sales worldwide (in billion USD)

II. CROWDSOURCING LAST MILE DELIVERY: STRATEGIC IMPLICATIONS AND FUTURE RESEARCH DIRECTIONS

A version of this chapter was published by Vincent E. Castillo, John E. Bell, William J. Rose, and Alexandre M. Rodrigues:

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This article originated in John Bell's Supply Chain Analytical Modeling seminar in Spring 2015. Over the following year, I continued working on the project after the class in terms of building the simulation model, designing the experiment, developing the theoretical basis, and drafting the initial manuscript. After the first manuscript was drafted, the co-authors (John Bell, Bill Rose, and Alex Rodrigues) helped to refine the document and prepare it for submittal. The first submittal to *Journal of Business Logistics* occurred on April 29, 2016 and after three rounds of reviews, received full acceptance on August 9, 2017.

Abstract

The rise of e-commerce over the past twenty years has created an increased need for responsive omnichannel distribution to meet the last mile challenge. Some companies are experimenting with the use of the sharing economy business model to augment distribution strategies. The use of so-called “Crowdsourced Logistics” (CSL) is becoming more prevalent in practice, but the role in logistics strategy of this new phenomenon has not been thoroughly investigated and understood. Using a contingency theory lens, this research contributes a nascent understanding of how CSL performs in terms of logistics effectiveness by simulating same-day delivery services from a distribution center to 1000 customer locations throughout New York City under dynamic market conditions and by comparing the results to those of a traditional dedicated fleet of delivery drivers. The findings are analyzed to suggest how firms may find strategic benefit by using CSL. An agenda for future research is provided to explore these strategic implications and to deepen knowledge about the CSL phenomenon.

Introduction

Over the past twenty years, the rapid growth of e-commerce has led to an evolution in supply chain management strategy and practice (Ta et al. 2015; Peinkofer et al. 2015; Bell et al. 2014; Brynjolfsson et al. 2013). Customers increasingly require anytime, anywhere demand fulfillment, necessitating improved inventory management and distribution strategies (Napolitano 2013). In response, companies seek to integrate innovative transportation technologies into existing distribution systems. One such innovation emerges from the "sharing economy" class of business models, offering multiple users temporary asset ownership benefits at a reduced cost (Howe 2006; Lamberton and Rose 2012; Miller 2013). One of the most popular models is ridesharing, facilitated by companies such as Über and Lyft, which distribute costs and benefits by connecting independent car owners and passengers via a mobile or computer application. Large firms, including Amazon and UPS, are increasingly investing in adaptations of the ridesharing service model to perform same-day delivery services, a phenomenon colloquially known as "Crowdsourced Logistics" (CSL) (AmazonFlex 2016; Supply Chain 24/7 2016; Savelsbergh and Von Woensel 2016). In the CSL business model, a shipper procures transportation services via a mobile or computer application directly from members of the crowd who provide those services as an independent contractor using a personally owned vehicle asset.

CSL relates to several emerging areas in supply chain research. For example, omnichannel distribution research lends insight into how firms simultaneously manage in-store and online channels to create customer value (Neslin et al. 2006; Verhoef et al. 2015). The quality of physical distribution service (PDS) (Rabinovich and Bailey 2004; Rabinovich et al. 2008) and effective returns management can improve online retailer performance (Griffis et al. 2012a; Rao et al. 2014). Additionally, reductions in order fulfillment cycle time enhance customer referral behavior, thus leading to increased firm performance (Griffis et al. 2012b). Common across these research efforts is the examination of logistics effectiveness in an e-commerce context. CSL relates to these research streams as a transportation mode within the last mile logistics strategy, but one whose impact on logistics effectiveness has not been fully examined in supply chain literature. Thus, the goal of this research is to compare CSL's logistics effectiveness as a last mile delivery mode to that of traditional dedicated delivery modes. In pursuit of this goal, the following research question is asked: *How does a crowdsourced fleet compare to a traditional dedicated courier fleet in terms of logistics effectiveness under dynamic task environment conditions?*

Related academic disciplines provide relevant work for initiating this research effort. Operations researchers have compared owned and outsourced transportation assets (Hoff et al. 2010) but this research tends to be concerned with cost minimization or fleet mix optimization rather than logistics effectiveness (Saunders et al. 2015). Additionally, most related vehicle routing research has not explored the effect of uncertainty in the supply of drivers, which characterizes CSL (Eksioglu et al. 2009; Lahyani et al. 2015). Furthermore, previous logistics research on same-day delivery services has demonstrated that task environment conditions, such as delivery windows and demand fluctuations, affect performance (Boyer et al. 2009; Campbell and Savelsbergh 2005). However, this research also does not explore these task environment conditions' impact alongside a resource constraint (such as vehicle supply uncertainty) on strategy and performance (Autry et al. 2008). Thus, there is a gap in academic knowledge with respect to logistics effectiveness associated with dynamic market conditions and the uncertain resource supply present in the sharing economy (Hossain and Kauranen 2015). As a result, the current research uses contingency theory (Drazin and Van de Ven 1985) to connect logistics strategy with task environment conditions and uncertainty in a supply of logistics assets (Autry et al. 2008).

Examining CSL for same-day delivery services under various environmental conditions answers Hossain and Kauranen's (2015) call for understanding crowdsourcing's strategic implications by comparing potential benefits and risks. Crowdsourcing provides a quick means of performing deliveries since drivers are independent contractors using personally owned vehicles to provide logistics services. However, since crowdsourced drivers manage their own schedules, CSL increases uncertainty relative to more stable dedicated vehicle fleets with known capacities and availabilities (Karger et al. 2011; Ndubisi et al. 2016). This form of resource sharing, or collaborative consumption, distributes costs and benefits across multiple users (Cohen and Kietzmann 2014), but the crowd (i.e., specific crowd members) chooses whether or not to provide the firm with a strategic resource (Daft et al. 1988). This makes the crowd both an uncontrollable environmental factor and a potential structural resource, thus increasing uncertainty and risk (Drazin and Van de Ven 1985; Daft et al. 1988). As collaborative consumption grows more popular among consumers (Matzler et al. 2015), the efficacy of crowdsourced services, such as logistics, should be explored more thoroughly to understand how they can contribute to customer value (Hossain and Kauranen 2015) and how certain task environment conditions affect the creation of customer value (Venkatraman 1989).

In exploring CSL's impact on logistics effectiveness under certain task environment conditions, we make three contributions to supply chain literature. First, we develop a systems-level understanding of the CSL phenomenon as a component of a firm's last mile distribution strategy. Second, we suggest how CSL can be leveraged strategically by comparing logistics effectiveness of a crowdsourced fleet of delivery drivers characterized by high vehicle supply uncertainty to that of a dedicated fleet of drivers with low vehicle supply uncertainty. Finally, we present a future research agenda to stimulate further investigation of the CSL phenomenon.

To make these contributions, we perform a stochastic discrete event simulation model informed by secondary data and discussions with managers from courier companies in major American cities (Bowersox and Closs 1989; Goldsby et al. 2006). Drawing upon previous research on both courier (Gendreau et al. 2006; Van Hentenryck and Bent 2006) and same-day delivery services (Boyer et al. 2009; Campbell and Savelsbergh 2005), we introduce vehicle supply uncertainty to compare CSL's performance with that of a traditional, dedicated fleet and to assess how the organizational task environment affects this relationship. We also conduct an exploratory post hoc analysis to further explore the relationship between the uncertainty associated with a supply of crowdsourced drivers and logistics effectiveness.

The remainder of this article briefly reviews previous research relevant to this study, which is followed by hypotheses development. The simulation model development process (SMDP) is then described, followed by the exploratory post hoc analysis. A discussion of the simulation's results and implications for theory and practice follow. Finally, we present a future research agenda for improving understanding of CSL for last mile distribution.

Literature Review

This study of the CSL phenomenon can be informed by literature in the last mile logistics, transportation brokerage, crowdsourcing, and vehicle routing research streams. Scholars have been considering last mile transportation's importance in distribution strategies since e-commerce's initial rise to prominence in the late 1990s and early 2000s. Bridging the last mile is considered critical to the online shopping experience and to developing effective distribution strategies (Lee and Whang 2001; Esper et al. 2003; Boyer and Hult 2005; Kull et al. 2007; Boyer et al. 2009). More recently, scholars have examined the state of omnichannel management (e.g., Herhausen et al 2015; Mena and Boulakis 2016; Ishfaq et al. 2016; Hübner et al. 2016), which encompasses last mile transportation, however, CSL's role in such strategies has yet to be explored.

Because CSL is enabled through creating electronic exchange markets, literature on transportation brokerage also provides reference points for how scholars may think about the CSL phenomenon. Electronic Transportation Markets (ETMs) facilitate transactions between buyers and sellers of transportation services, resulting in lower information-seeking, bargaining, and policing/enforcement costs (Beilock and Shell 1992; Goldsby and Eckert 2003). Companies that create mobile or computer-based applications to connect buyers and sellers of transportation services (i.e., crowd members), such as Postmates or Deliv, act as transportation brokers, providing similar benefits to those of ETMs for last mile delivery in exchange for fees. Like most transportation brokerage firms, the creators of applications for CSL typically do not have many assets (Ashenbaum et al. 2012); but a main difference of CSL applications is the supply chain tier where the purchased transportation is provided. Transportation brokerage firms typically focus on upstream movement of goods between, for example, suppliers and manufacturers. The related research focusing on B2B exchange, however, does not account for either a new social dimension or the uncertainty associated with crowdsourcing individual delivery agents (Ta et al. 2015).

Unfortunately, sourcing from the sharing economy for distribution introduces additional risk (Ndubisi et al. 2016). While CSL can facilitate collaboration among a retailer, independent delivery agents, and the consumer, it also introduces competitive consumption. Firms seeking delivery agents compete not only with each other, but with drivers' other interests and needs. CSL also introduces vehicle supply uncertainty not found in a privately-owned fleet because drivers manage their own schedules and work as long or as little as they desire. As a result, the decision to use CSL involves navigating a trade-off between cost and uncertainty. Furthermore, the comparison between CSL and a dedicated fleet is complicated by environmental factors, such as demand and time windows, which can moderate the association between vehicle supply uncertainty and logistics performance.

Operations researchers have explored the trade-offs between owning and outsourcing transportation as part of the fleet mix problem (Hoff et al. 2010). These problems seek the most efficient combination of finite resources, such as vehicles or technicians, required to serve a customer population. A literature review reveals several variants on the basic scenario, including fleet mix problems with demand variation (Topaloglu and Powell 2007), vehicle leasing and ownership costs (Shyshou et al. 2010), and multiple starting and ending points (Godfrey and Powell 2002). A set of models also explores variation in fleet size and mix, but both assume new vehicles will be purchased outright (Bakkehaug et al. 2014) or leased from a spot market for a set time period (Gundegjerde et al. 2015). In CSL, on the other hand, drivers are employed by task instead of time (Kittur et al. 2008), allowing firms to avoid fixed costs, empty moves, and idle-time expenses. Furthermore, task-based contracts result in a lack of dedicated vehicles and an uncertain driver pool for upcoming orders. As fleet availability directly affects associated vehicle routing problems (Hoff et al. 2010), an uncertain fleet mix adds complexity to logistics decision-making.

Of the many variants of Dantzig and Ramser's (1959) classic vehicle routing problem (VRP), CSL most closely aligns with the "courier problem." This problem is characterized by delivery of small packages or parcels within tight time windows where customer locations are unknown a priori and delivery requests arrive dynamically and stochastically throughout the workday (Toth and Vigo 2001; Mitrović-Minić et al. 2004; Gendreau et al. 2006; Van Hentenryck and Bent 2006; Lahyani et al. 2015). Additional studies on the courier problem in operations research literature include vehicle fleet variations necessitating different approaches to delivery route planning. Those differences include comparing fleets of capacitated and uncapacitated vehicles, heterogeneous and homogeneous vehicle fleets, fixed and unlimited number of vehicles, and the effects of those differences on route planning practices (Eksioglu et al. 2009; Lahyani et al. 2015). However, neither the vehicle routing literature nor the supply chain literature discusses the performance impacts of vehicle supply uncertainty.

This literature review highlights how our examination of CSL builds upon accumulated research in the last mile logistics, transportation brokerage, crowdsourcing, and vehicle routing domains of supply chain management. Firms considering CSL should account for many factors, such as the development of supply management strategies for ensuring suitable availability of crowdsourced drivers, or the customer service implications of using amateurs as frontline employees. However, these factors cannot be effectively assessed without understanding how CSL can fit into a last mile distribution strategy based on how a fleet of crowdsourced drivers performs relative to a dedicated fleet of drivers. Therefore, we develop hypotheses to better clarify the logistics performance implications of using a crowdsourced fleet under different market conditions.

Hypotheses Development

Contingency theory provides a valuable lens through which to analyze the logistics effectiveness (i.e., performance) of a crowdsourced fleet of delivery drivers. Contingency theorists argue that an organization's environment moderates the relationship between its design and performance (Drazin and Van de Ven 1985; Prescott 1986, Rosenzweig 2009; Van de Ven et al. 2013). In other words, performance is a function of organizational design and its interaction with organizational environment (Venkatraman 1989); and the level of achieved performance is contingent on the coalignment, or fit, between the strategy and the external environment (Venkatraman and Prescott 1990). This research compares each fleet type's logistics effectiveness as a component of logistics performance, which has been demonstrated to have a positive association with firm performance (Mentzer and Konrad 1991; Langley and Holcomb 1992; Rabinovich and Bailey 2004; Rabinovich et al. 2008; Fugate et al. 2010).

Organizational design refers to the strategy employed or the organization's internal configuration (Van de Ven et al. 2013), which in this research refers to using a dedicated fleet or a crowdsourced fleet of delivery drivers. The organizational environment refers to external physical and social factors affecting decision-making within the firm (Daft et al. 1998). More specifically, we consider the task environment, which are those factors affecting day-to-day operations (e.g., competitors; suppliers; or in the case of this research, customers) (Daft et al. 1998). These contingency theory components are described in the development of hypotheses (depicted in Figure 2[a]) used to compare a crowdsourced fleet's logistics effectiveness to that of a dedicated fleet of delivery drivers.

Previous supply chain research has defined logistics performance as including a logistics effectiveness component (Fugate et al. 2010; Langley and Holcomb 1992; Mentzer and Konrad 1991). Logistics effectiveness is the extent

[a] All figures and tables are provided in the Appendix for this chapter.

to which logistics goals are met and is measured by key performance indicators (KPIs), such as on-time delivery rate, order accuracy rate, and lead times (Mentzer and Konrad 1991). We focus this study on logistics effectiveness because the associated performance measures capture supply chain responsiveness (Christopher and Towill 2000; Gligor et al. 2015), a factor deemed critical to omnichannel strategies (Griffis et al. 2012a; 2012b; Rao et al. 2014).

The question of how same-day delivery services informed by a strategy using an uncertain supply of vehicles, such as a crowdsourced fleet, affects logistics effectiveness has not been examined analytically or empirically. However, previous research lends insight into theorizing about how a crowdsourced fleet with supply uncertainty may perform. For example, high uncertainty in product demand and supply markets can create supply chain inefficiencies (Xue et al. 2011; Stank et al. 2012; Gligor et al. 2015). Hoff et al. (2010) contend that high uncertainty may exacerbate an organization's ability to minimize a delivery fleet's transportation costs. Furthermore, introducing uncertainty is likely to negatively influence process effectiveness in general. Therefore, if a supply of vehicles has high uncertainty in terms of composition and availability, such as in a crowdsourced fleet, it is reasonable to expect that inefficiencies exist in the system and, thus, logistics effectiveness would be degraded.

While the negative association between uncertainty and effectiveness supports private fleet ownership over CSL, this supply risk only explains one aspect of performance variance (Wagner and Bode 2008). Following previous research, further exploration of task environment factors affecting logistics effectiveness becomes necessary (Yang et al. 1999; Yang et al. 2004). Contingency theory states that no single strategy provides optimal outcomes in all situations and that an organizational design's performance is contingent on contextual factors (Rosenzweig 2009). As a result, the specific contextual factors may enhance or reduce the negative impact of vehicle supply uncertainty on logistics effectiveness (Gligor et al. 2015; Van de Ven et al. 2013).

One such task environment factor is dynamism, i.e., fluctuations in demand and supply markets, changes in customer preferences, and the business environment's unpredictability (Wang et al. 2011). The environment in which this study takes place is that of a courier company offering same-day delivery services in an urban area. Two aspects of environmental dynamism that may affect the couriers' abilities to provide same-day delivery services are time windows for deliveries (Yang et al. 1999; Yang et al. 2004; Boyer et al. 2009) and dynamic demand fluctuations (Campbell and Savelsbergh 2005; Gendreau et al. 2006; Ghiani et al. 2009; Agatz et al. 2008). First, Boyer et al. (2009) noted in their study of same-day delivery services that increasing delivery time windows leads to more flexibility and route selection (i.e., broader time windows would allow better logistics effectiveness to be achieved). It is reasonable to hypothesize that the opposite is also true. Combining this perspective with the contingency theory implication that environmental factors may confound the negative performance effect of high vehicle supply uncertainty (Rosenzweig 2009; Van de Ven et al. 2013), the following hypothesis is made:

H1: Tight time windows negatively affect the relationship between a crowdsourced fleet and logistics effectiveness more so than they affect the relationship between a dedicated fleet and logistics effectiveness.

A second aspect of environmental dynamism that may affect a crowdsourced fleet's logistics effectiveness is demand variability (Campbell and Savelsbergh 2005; Gendreau et al. 2006; Ghiani et al. 2009). Demand variability can have stronger negative effects on utilization rates of delivery capacity in online channels compared to retail channels because of smaller transaction sizes and increased order frequencies (Agatz et al. 2008). Additionally, because supply risk and uncertainty reduce confidence in achieving a desired outcome (Zsidisin 2003), combining the effects of an uncertain supply of crowdsourced drivers with demand variability's negative impact, the deterioration of logistics effectiveness is likely to be increased. Consequently, the following hypothesis is presented:

H2: Greater demand variability negatively affects the relationship between a crowdsourced fleet and logistics effectiveness more so than it affects the relationship between a dedicated fleet and logistics effectiveness.

Methodology

Discrete event simulations have a rich history of use in supply chain management research, as this method provides a controlled environment in which to analyze phenomena from a systems perspective (Bowersox and Closs 1989; Größler et al. 2008; Evers and Wan 2012). This perspective provides the analyst with the ability to create models that can lead to a greater understanding of complex systems, such as supply chains (Bowersox and Closs 1989; Schwanginger and Grösser 2008; Manuj et al. 2009). Simulation has been used in SCM research to improve understanding of such phenomena as supply chain and inventory management strategies (Goldsby et al. 2006; Shapiro and Wagner 2009; Wan and Evers 2011) and supply chain risk management (Manuj et al. 2014; Käki et al. 2015). Because this research effort is exploratory and concerned with understanding CSL at a systems level, we developed a stochastic discrete event simulation to examine this phenomenon (McGrath 1982; Mentzer 2008). To ensure rigor in developing the model, we followed the Simulation Model Development Process (SMDP) developed by Manuj et al. (2009) and complemented it with guidance from Tersine (1993), Law and Kelton (2000), and Sargent (2005; 2013).

Problem Formulation.

The central problem in this simulation is comparing logistics effectiveness of a crowdsourced fleet of vehicles to that of a dedicated fleet of vehicles for same-day delivery. In this simulation model, effectiveness is operationalized in two forms: on-time delivery rate (Griffis et al. 2007; Gunasekaran et al. 2001) and total number of deliveries performed. By focusing on the crowdsourced fleet's logistics effectiveness, we can begin to theorize the situations in which CSL may be employed to support last mile strategies.

The simulation requires simplifying assumptions to increase tractability. The model simulates an intra-city courier service providing same-day delivery from a centralized distribution center (DC) in an urban customer network. As shown in Figure 3, we use Amazon's Manhattan fulfillment center as the centralized DC and 1000 addresses throughout New York City as the urban customer network. These customer locations are unknown a priori and arrive dynamically and stochastically throughout the day, thus emulating real-world same-day delivery services. Vehicle accidents or breakdowns are not included in the model. Driver diversions are not allowed; thus, once making a delivery, a driver cannot be diverted to make another pickup and delivery. In accordance with previous research on the courier problem (e.g., Sungur et al. 2010), packages are assumed to be small parcels; thus, vehicles are uncapacitated and one package is delivered per trip. Also, following Sungur et al. (2010), all requests are accepted and drivers travel at a constant speed throughout the customer network.

Variables.

The simulation has a 2x3x5 factorial design with one main independent variable, two moderating variables, and two dependent variables. Table 1 summarizes the variable definitions, measures, and sources. The independent variable is Fleet Type (FLT), and the moderating variables are Time Window Distribution (TWD) and Daily Demand Profile (DMD). Through consultations with practitioners, all variables were identified as being critical measures and concerns for courier operations as well as found in previous research on similar phenomena (e.g. Yang et al. 1999; Yang et al. 2004; Campbell and Savelsbergh 2005; Gendreau et al. 2006; Van Hentenryck and Bent 2006; Boyer et al. 2009).

The independent variable, FLT, is a binary variable that provides the means to compare a crowdsourced fleet to a dedicated fleet. The two levels represent the fleet types: crowdsourced (CS) and dedicated (DED). A CS fleet is the type that would be employed by AmazonFlex or an Über-for-logistics organization. CS drivers manage their schedules and are free to accept as many or as few deliveries as they desire. Thus, uncertainty in the supply of CS drivers is likely to be high throughout a workday relative to a DED fleet, found in a traditional courier company that owns and maintains its vehicle fleet to provide same-day delivery services. A DED fleet is characterized by a constant supply of vehicles throughout a workday.

The first moderating variable, TWD, refers to the levels of service courier companies typically offer for same-day deliveries. Three service levels are used in this simulation and listed in Table 2. These values are based on practitioner consultations and publicly available secondary data. Courier companies typically offer one-, two-, or four-hour time windows for same-day deliveries. Practitioners indicated that in a standard workday 50% of all on-demand (i.e., same- day) deliveries have a 1-hour time window request, 40% of requests will have a 2-hour time window service level, and the remaining 10% are asked to be delivered within 4 hours. This “standard” distribution represents the first level of the time window distribution variable, STD. Thus, the TWD variable’s STD level is 50%-40%-10%, indicating that 50% of all orders are to be delivered within one hour, 40% within two hours, and 10% within four hours. The second level, FLX, is based on same-day delivery service levels AmazonFlex offers. AmazonFlex offers two-hour delivery windows, but customers may select a one-hour delivery window for an added cost. Using simulation pretests to assess a probability distribution profile that produces realistic results, the TWD variable’s FLX level is set to 10%-90%-0%. The TWD variable’s third level seeks to provide insight into the hypothetical situation in which all customers request a one-hour delivery. This hypothetical profile was empirically inspired by discussions with practitioners to assess which fleet would be better able to handle high urgency levels in its customer base. This level of the TWD variable represents maximum urgency of all customers (MAX) and is 100%-0%-0%.

Two dependent variables were used for this simulation: On-Time Delivery rate (OTD), and Total Deliveries (TD). OTD was selected as a measure of logistics effectiveness based on practitioner discussions because it is a central performance measure for same-day courier operations. The second dependent variable, TD, was added to further explore the impact of vehicle supply uncertainty on logistics effectiveness and to increase this study's explanatory power. These measures allow for meaningful comparison of the two fleet types in terms of logistics effectiveness.

Model Development and Conceptual Validation.

Based on discussions with practitioners and consultations with experienced academics, a conceptual simulation model was developed. Two flow charts are depicted in Figure 4 to represent the key changes between the DED and CS fleets. In both fleets, the simulation starts with a customer request for a delivery arriving in accordance with one of the five daily-demand profiles (listed in Table 2). After a request is received, two attributes are assigned: a time window in accordance with one of the three TWD profiles, and a distance to be traveled from the distribution center to the customer location. Once these two attributes are assigned, the order is held at the distribution center until a driver is available to pick up and deliver the order. After completing the delivery, the driver returns to the distribution center to make another delivery.

The two fleets vary at two points in the simulation. First, the number of vehicles available at the start of the simulation are different based on pretesting in which the minimum number of vehicles is selected that allows for continuous deliveries to be made and that avoids a backlog of orders that cannot be filled. That is, the parameter of starting vehicles per fleet was chosen to prevent the simulation from stopping because packages are unable to exit the system. Second, the fleet types also differ at the end of the process when a delivery is completed. CS drivers decide whether they accept another delivery, whereas DED drivers do not have this ability. A follow-up delivery acceptance rate of 75% was selected based on information provided by a company facilitating restaurants' use of CSL for on-demand food deliveries. The company explained that it guaranteed CSL drivers a minimum wage per hour if they accepted 75% of all deliveries available to them in a given day. The delivery acceptance rate is important to a CS fleet's logistics effectiveness. The next section explores the acceptance rate's implications more deeply in a post hoc analysis.

Validation of this conceptual model was performed in accordance with procedures established by Sargent (2005). Conceptual Model Validation is achieved by ensuring that the underlying theories and assumptions are correct and that the model representation is reasonable for the problem being studied (Sargent 2013). Two of Sargent's (2005) 16 techniques were used to validate the conceptual model: Face Validation and Traces. Face Validation requires expert consultation to assess if the model's behavior and output are reasonable. Academics not associated with the research project but knowledgeable in last mile distribution research and practice confirmed the model was reasonable. Traces were used to follow the simulation entities (i.e., orders and drivers) through the system and to ensure the logic was correct. Both techniques provided sufficient evidence of Conceptual Model Validation.

Data Collection.

Data for the simulation were acquired through discussions with practitioners in San Francisco, Dallas, Nashville, and other major American cities; publicly available secondary data sources; and previous literature. Initially, the model was built and validated using Solomon's (1987) random-clustered customer network for the vehicle routing problem (VRP). Customer locations and distances from a central distribution center were used in assigning package attributes described in the previous section. Once validated, the customer network depicted in Figure 3, representing the New York City (NYC) metropolitan area, was used to run the actual simulation and statistical analyses. The NYC government provides a publicly available database of 94,000 business and residential addresses throughout the city on its open data website (https://nycopendata.socrata.com/), of which one thousand were randomly selected. We then calculated the rectilinear distance for each address from Amazon's Manhattan distribution center. An equal probability for each of the 1,000 distances was applied to the final simulation.

The number of crowdsourced drivers available changes dynamically throughout the day. The distribution used in the simulation was derived from the New York City Taxi Limousine Commission's (TLC) annual report, which quantifies the average supply of taxi drivers available per square kilometer in NYC at any given time throughout the week (NYC TLC 2015). The Poisson intensity parameters used to operationalize the CS driver supply in the simulation are reported in Table 1.

Computer Model Verification and Validation.

Verification and validation of the computer model were also achieved in accordance with procedures established by Sargent (2005; 2013). Four steps comprise the verification and validation process. The first is Conceptual Model Validation, described in the preceding section. The second is Computerized Model Verification, the conceptual model's correct programming and implementation (Sargent 2005; 2013). Three of Sargent's (2005) 16 techniques were used to verify the computer model: Face Validation, Degenerate Tests, and Animation. The simulation model was developed iteratively in ExtendSim 9 (Imagine That! Inc. 2013), with each added step increasing the model's complexity. Incremental additions to the computer model were made and Face Validity was verified by experts not involved with the research project. Degenerate Tests were performed to ensure that new additions to the model resulted in expected tasks being performed. For example, when changing demand profiles from a baseline case (e.g., UNI) to a more intense case (e.g., ACT), the number of orders queued should rise; this behavior was verified in the simulation. Two-dimensional Animation was also used to visually verify that the modeled behavior matched the expected behavior.

The third step in the validation and verification process is to assess Operational Validity, defined as the evaluation that the model is sufficiently accurate for its intended purpose (Sargent 2005; 2013). The Internal Validity technique was used to assess Operational Validity, along with the Parameter Variation-Sensitivity Analysis and Face Validation techniques. Internal Validity refers to the amount of stochastic variability within the model across runs, with high amounts of variability implying inconsistency (Sargent 2005). Internal Validity was confirmed by performing multiple runs using Solomon's (1987) random-clustered (R-C) customer network in place of the NYC customer network. The results in the dependent variables using the Solomon network were consistent across runs. This consistency was replicated when substituting the NYC customer network for Solomon's R-C network. Parameter Variation-Sensitivity Analysis consists of changing input values and assessing the effects on output values and the system's behavior. For example, by decreasing the dedicated delivery fleet's size, the fleet's logistics effectiveness should decrease as well. This expected behavior was observed such that the system's ability to fill orders on time was deteriorated as the number of dedicated drivers was reduced. Lastly, Face Validation was also confirmed by consulting with experts not directly associated with the research project.

The final step in the verification and validation process is to assess Data Validity, or that the data used to build, evaluate, and conduct the experiments are adequate and correct (Sargent 2013). Two of Sargent's (2005) techniques were used: Historical Data Validation and Parameter Variation-Sensitivity Analysis. Historical Data Validation refers to the use of one portion of a historical dataset to develop the model and the remaining data to run the experiments. We adapted this approach by developing the simulation using Solomon's (1987) R-C customer network and then running the experiments using the rectilinear distances from the NYC customer network depicted in Figure 3. We also collected data to use for parameters by meeting with practitioners, as described in a preceding section. These empirically-inspired distributions were then subjected to the Parameter Variation-Sensitivity Analysis technique by changing their values and comparing the resulting effects on TD, OTD, and TDPD. The four-step verification and validation process provided sufficient evidence that the model was reasonable for comparing a crowdsourced logistics fleet to a dedicated fleet of drivers in terms of logistics effectiveness.

Simulation.

The sample size (N=750) was determined in accordance with established procedures by Tersine (1993) and Law and Kelton (2000). Trial runs were performed, and the number of runs per scenario was calculated using the resulting means and standard deviations with a desired 5% relative-precision level, resulting in a need for 25 runs for each of the 30 scenarios. Demand was generated during an average workday from 0700 – 1600 hours; the run length was set to 30 days, allowing for analysis of a standard contract length for the assignment of a dedicated fleet of about 2-3 weeks (Rajapakshe et al. 2014). This run length also provided enough data to discard the warm-up period, which was set to 2.5 days, the time during which the dependent variables' transient distributions converged into steady-state behavior (Law and Kelton 2000).

Analysis and Results.

Using SPSS 24, pairwise t-tests were performed to test the null hypothesis that no significant differences exist in logistics effectiveness between the fleet types under varying time windows and demand conditions at the 5% significance level. Violation of the assumption of multivariate normality was assessed by visually inspecting the data. The Kolmogorov-Smirnov (K-S) test could have been used (as could skewness and kurtosis analysis); but due to the sample size (N=750), the K-S test would likely detect small deviations from normality that would not have a practical effect on the analysis (Field 2009). Visually inspecting each dependent variable's distribution verified that the data were in fact normally distributed within each group; thus, the assumption of dependent variable normality was not violated.

The pairwise t-tests provided mixed results for the hypotheses that the task environment moderates the relationship between fleet type and logistics effectiveness. The results are listed in Table 3. H1 suggested that time windows would be more detrimental to a crowdsourced fleet's logistics effectiveness than to a dedicated fleet's. The results indicated that time windows more strongly reduced logistics effectiveness as measured by On-Time Delivery (OTD) rate for a crowdsourced fleet than for a dedicated fleet in all three levels of the TWD moderating variable (Δ_{Mean}, t-statistics, and 95% confidence intervals of the difference of means are provided in Table 3). However, a significant moderating effect was not found when operationalizing effectiveness as Total Deliveries (TD). Thus, partial support was found for **H1.** The interaction plots of the significant TWD profiles are provided in Figure 5a in the Appendix.

H2 suggested that greater daily-demand variability would be more detrimental for a crowdsourced fleet's logistics effectiveness than for a dedicated fleet's. The results of the analyses showed that only the Actual and Extreme surge daily-demand profiles had statistically significant moderating effects on the relationship between fleet type and OTD (see Table 3 for results). Under both demand profiles, the dedicated fleet's OTD was better than the crowdsourced fleet's, and there was greater deterioration in logistics effectiveness for the crowdsourced fleet. For the TD dependent variable, while the Actual and both Extreme profiles were statistically significant, the Extreme-Morning profile showed the greatest difference in logistics effectiveness between fleet types. The crowdsourced fleet could provide more Total Deliveries than the dedicated fleet could, but not all demand profiles resulted in significant differences. These mixed results provide partial support for **H2.** The interaction plots of the significant DMD profiles are provided in Figures 5b and 5c in the Appendix.

Post Hoc Analysis

An exploratory post hoc analysis was performed to seek additional insights about the uncertainty surrounding a supply of crowdsourced drivers. One unique attribute of CSL is the control drivers have over their schedules; i.e., they are free to make as many or as few deliveries as desired. The rate at which drivers continue to remain available for additional deliveries is known as the follow-up delivery acceptance rate. This rate is important because it affects the delivery fleet’s capacity, in turn potentially affecting logistics effectiveness.

Ridesharing companies, such as Über and Lyft, manage the delivery acceptance rate and the supply of drivers through surge pricing strategies that increase during periods of peak demand or within geographical regions with higher-than-average demand levels. Thoroughly understanding such supply management strategies is critical to effectively and efficiently using a crowdsourced fleet. Surge pricing, which should be considered a component of a supply management strategy, can increase or decrease a crowdsourced fleet’s capacity, which in turn should also affect logistics effectiveness based on the number of available delivery agents. This post hoc analysis explores the latter relationship between the crowdsourced fleet’s capacity and logistics effectiveness by examining the impact of different follow-up delivery acceptance rates on TD and OTD. We hypothesize that the follow-up delivery acceptance rate is positively associated with logistics effectiveness such that as the follow-up acceptance rate declines, so too will effectiveness because fewer drivers will be available to make same-day deliveries.

A 3x2 factorial design was chosen to explore this hypothesis. The first factor is the TWD variable used in the main study and consists of three levels, as described in Table 2. This factor was chosen to consider different levels of urgency of same-day delivery orders. The second factor is the crowdsourced driver delivery acceptance rate. This factor has two levels – 75% and 25% – representing the percentage of drivers who accept another job upon completing their current assignment. This factor was manipulated in the last step of the crowdsourced model simulation flow chart shown in Figure 3. To capture the most realistic results, the six scenarios were run under the “Actual” daily-demand profile. Logistics effectiveness was operationalized as TD and OTD, as in the main study; but only the results for OTD were found to be significant.

Table 4 provides the descriptive statistics and analysis results. Only the results for the OTD outcome variable are reported because the expectation that logistics effectiveness deteriorates under lower follow-up delivery acceptance rates was only supported on the OTD dependent variable. No significant relationship was found for TD. Furthermore, the results for OTD present a particularly intriguing relationship.

A pairwise t-test performed in SPSS 24 was used to compare mean OTD when the acceptance rate is 75% versus 25%. The results support the hypothesis that as the crowdsourced driver's follow-up acceptance rate declines, logistics effectiveness also deteriorates (see Table 4 for t-statistics and significance levels). This finding is consistent across all three levels of the TWD variable. To further explore this finding and more deeply understand the relationship, additional rates were entered into the simulation and the resulting OTD were then plotted as a function of follow-up acceptance rates (See Figure 6 in Appendix).

The interaction plot in Figure 6 reveals that as delivery acceptance rates drop from 100% to 75%, the negative impact on OTD appears to be minimal. However, as the acceptance rate falls below 75%, OTD is more negatively affected because of the smaller fleet capacity. This negative relationship continues until the delivery acceptance rate reaches 50%, where the OTD begins to improve. This relationship is somewhat misleading, however, because the improvement in OTD is likely a result of a crowdsourced fleet's reduced capacity. That is, when the acceptance rate falls to 50%, the crowdsourced fleet can make fewer total deliveries; but this is inversely proportional to OTD (see Table 1 for calculation of OTD). Therefore, as the total number of deliveries performed begins to drop OTD becomes inflated. This effect is discussed in more detail in the following section.

Discussion

Consistent with contingency theory, the main analysis results provide evidence that the organizational task environment moderates the relationship between delivery fleet types (in terms of crowdsourced vs. dedicated vehicles) and logistics effectiveness (Miller 1992; Venkatraman 1989). Furthermore, the difference in effectiveness between the two fleet types suggests there are conditions in which one fleet type exhibits better fit with the task environment than the other; that is, one fleet type performs better than the other. More specifically, the simulation suggests that a dedicated fleet of drivers is more likely to have better on-time delivery rates than a crowdsourced fleet across various time windows and demand profile combinations; but there are scenarios in which a crowdsourced fleet can perform more total deliveries than a dedicated fleet. In other words, a retailer seeking to adopt a crowdsourced logistics strategy needs to be concerned with poor OTD of same-day deliveries. However, under certain environmental conditions, a retailer can potentially fill more orders than a dedicated fleet because a crowdsourced fleet is a low fixed-cost option that does not have the same capacity limit as a dedicated fleet.

Because a crowdsourced fleet may perform more total deliveries than a dedicated fleet (although at a lower OTD), the study also suggests that crowdsourced logistics (CSL) may best fit delivery situations in which time sensitivity is not the greatest concern. For example, time sensitivity is less critical in the reverse supply chain; therefore, CSL may be an effective solution to increase velocity of returns to the point of disposition (Mollenkopf et al. 2011). Furthermore, because returns for online shoppers can occur at a rate double that of in-store customers (Bernon et al. 2016), firms seeking to recapture value in the reverse supply chain may benefit from using CSL for returns management.

Next, the finding that a crowdsourced fleet performs more total deliveries implies that CSL may also be best used as excess capacity. CSL may increase the agility of the supply chain in the last mile by gaining a buffer for unexpected surges in demand (Christopher and Towill 2000; Gligor et al. 2015). The deliveries performed with a CSL fleet might have worse OTD, but might provide a suitable backup plan.

Finally, the results of the post hoc analysis show a positive curvilinear relationship between the follow-up delivery acceptance rate of crowdsourced drivers and the fleet's logistics effectiveness. The curve's shape suggests there is a point where a declining follow-up acceptance rate of a crowdsourced fleet can become severely detrimental to its logistics effectiveness, shown in Figure 5 as around 75%. However, it appears that the inflection point where OTD begins to become positive is a result of the measure's being inversely proportional to the total number of deliveries performed, which in turn is a function of the number of crowdsourced drivers available. That is, if fewer drivers are available, fewer total deliveries may be performed. This finding conveys the importance of monitoring two characteristics of a crowdsourced fleet: current size and delivery acceptance rates. By continuously monitoring CSL fleet size and delivery acceptance rates, firms may gain the ability to anticipate when logistics effectiveness might be negatively impacted and, in turn, trigger surge pricing or other supply management strategies. Therefore, developing effective crowdsourced driver supply-management strategies that maximize the follow-up job acceptance rate is critical.

Theoretical Implications.

This research has several theoretical implications. First, a growing body of literature in diverse fields – such as anthropology, information systems, and strategic management – underscores heightened academic interest in the sharing economy. However, practical guidance on capturing value through crowdsourcing remains underdeveloped (Hossain and Kauranen 2015). Our research helps fill this gap by examining the fit between a crowdsourced logistics strategy and certain market conditions. Furthermore, this research uses a simulation model to explore contingency theory hypotheses, answering a call from previous researchers to further examine the theory that the relationship between organizational design and performance is contingent on the environment (Van de Ven et al. 2013). We find support for this theory in the context of crowdsourced logistics and the task environment.

Our findings also advance fleet management and vehicle routing research that typically focuses on cost minimization (Saunders et al. 2015). By integrating vehicle supply uncertainty into a fleet management decision, the simulation highlights the importance of effectiveness outcomes, such as on-time delivery rates and total deliveries. Additionally, CSL reduces dependence on the resource-intensive and complex fleet sizing problem (Rajapakshe et al. 2014), while increasing responsiveness in the supply chain (Gligor et al. 2015).

Managerial Implications.

This research makes several managerial implications to help clarify when CSL may be best used, but further research is needed. Crowdsourced fleets may have lower on-time delivery rates than dedicated fleets, but may perform more total deliveries (TD) under some demand conditions. As a result, managers should deploy CSL strategies when lateness penalties are less severe to maximize total deliveries but minimize poor performance consequences. CSL also appears to provide means for increasing agility and responding to sudden demand surges. Thus, when demand unexpectedly spikes and exceeds the dedicated fleet's capacity, turning to CSL enables deliveries to continue being made, albeit with degraded on-time delivery rates. Additionally, tardiness in the reverse supply chain may not be as critical as in the forward supply chain. Therefore, retailers may find benefit in using CSL to reacquire returns or end-of-life goods to the point of disposition where value is recaptured (Mollenkopf et al. 2005; Mollenkopf et al. 2007). Finally, this research implies that firms seeking to adopt CSL should carefully monitor the crowdsourced drivers' delivery acceptance rates to be ready to trigger surge pricing or other aspects of a supply management strategy in the event the rate falls below acceptable levels.

Limitations.

Research limitations exist as a result of the methodology chosen to compare logistics effectiveness of CSL and dedicated delivery fleets. First, a computer simulation was performed in pursuit of generalizable findings at a systems level (McGrath 1982). In this pursuit, behavioral variables (e.g., how and why crowdsourced drivers accept follow-on jobs and the related supply management strategies) are not considered, but may affect a crowdsourced fleet's performance. Second, the archival nature of the data used to operationalize the supply of crowdsourced drivers (i.e., available taxi drivers in NYC) also limits the simulation's precision, as do the assumptions made to increase the model's tractability; however, the findings allow for initially understanding CSL as a system. Finally, while we found statistically significant differences in the two fleet types' logistics effectiveness under different scenarios, the practical significance of the differences is potentially limited, which is inherent to computer simulation modeling in general. To minimize this limitation, we used empirical distributions and parameters wherever possible to increase realism and practicality. Nevertheless, future research should emphasize the importance of empirical data collection and analysis to maximize not only research validity but also practical relevance.

Future Research.

A plethora of future research opportunities exist that would allow researchers to expand beyond these limitations. Furthermore, because CSL is a nascent phenomenon becoming increasingly prevalent in practice, future research building on the current findings may also provide supply chain scholars with means to begin leading practice (Goldsby and Zinn 2016). Table 5 summarizes potential opportunities for analytical, empirical, and qualitative research.

While this simulation compared two types of fleets under varying market conditions, a hybrid fleet of dedicated and crowdsourced drivers may exhibit a better environmental fit than homogeneous fleets of one type or the other. Thus, one important future research avenue is to explore how firms can approach the fleet mix optimization problem, which is related to the fleet sizing problem (Rajapakshe et al. 2014). Optimization or metaheuristic algorithms could be combined with a computer simulation to develop probabilistic relationships between fleet mix levels and organizational environment characteristics, resulting in better understanding of how managers can leverage the CSL phenomenon to improve firm performance.

Along with introducing a hybrid fleet, adding processes and structures to the model, such as surge pricing, would facilitate a systems approach to contingency theory testing (Drazin and Van de Ven, 1985) and to integrating general systems theory (von Bertalanffy 1950). Using a contingency systems perspective

(Venkatraman 1989) would allow the research to examine more complex strategies employed in response to environmental factors and vice versa. The basic simulation model presented in the current research can be expanded to incorporate these and other factors to provide a more holistic view of the logistics operation and its task environment.

Research on crowdsourcing agrees that the crowd's motivation should be understood prior to sourcing from it (Chandler and Kapelner 2013; Hossain and Kauranen 2015). In an ethnography of drivers who contract with Über and Lyft to provide ridesharing services, Anderson (2014) found three types of drivers, varying on why and how often they drive for Über. More recently, Rosenblat (2016) and Rosenblat and Stark (2016) also found a range of driver motivations, from being underemployed to wanting to grow their social network. While both studies were in the context of ridesharing and not in moving goods, both suggest the potential for a typology of crowdsourced logistics driver. Understanding how and why crowdsourced drivers do what they do may help develop more nuanced and potentially more effective supply management strategies. Therefore, a phenomenological or ethnographical approach would serve in understanding this critical component of crowdsourcing for logistics.

Future research can also explore more deeply the issues arising from managing a supply of crowdsourced drivers. For instance, one issue is how firms can maximize fit between supply management and demand management strategies (Esper et al. 2010) when crowdsourcing delivery agents or other assets. A dispatcher responsible for managing the fleet of crowdsourced drivers tracks changes in not only demand, but also driver supply. Thus, a critical question emerges regarding how to integrate demand and supply to enhance firm performance. This question could be explored through developing supply elasticity curves based on driver payments and demand patterns, which could form the basis of surge pricing that can increase the supply of crowdsourced drivers as needed.

The potential performance benefits and strategic implications a company might gain are limited by additional risks to mitigate when choosing to crowdsource a delivery driver fleet. For example, security and insurance for deliveries require additional, potentially costly investments (Williams et al. 2008). Also, crowdsourced delivery drivers become de facto frontline employees; so their effect on brand image should be considered along with how to promote brand-building behavior (Morhart et al. 2009; Dagger et al. 2013). Therefore, future research should also examine supply chain security and brand management implications along with potential agency issues associated with CSL.

Finally, while this research effort was concerned specifically with applying sharing economy business models for last mile logistics in a B2C context, strategies are emerging in the B2B context in the upstream supply chain. For example, some companies (e.g., Cargomatic, TransFix, and Lane Honey) have adapted CSL as a modern electronic-transportation market to facilitate acquisition of truck-load and less-than-truckload transportation services. Other companies like Flexe provide a service similar to Airbnb's in the warehousing space. Thus, future research should explore these areas as well to further understand issues arising when supply chains pass through the sharing economy.

Conclusion

This paper makes three contributions in an initial step toward a deeper understanding of crowdsourced logistics (CSL). First, a high-level perspective of CSL is introduced. Using crowdsourced delivery agents to fill online orders over the last mile allows retailers to quickly gain access to transportation but requires considering a new social dimension and uncertainty not present in B2B relationships. Additionally, CSL's growth in urban areas increases transportation diversity in distribution channels, enabling firms to capitalize on the sharing economy in which congestion and lower access to resources may limit traditional last mile strategies (Rose et al. 2016). Thus, CSL represents an addition for last mile distribution, especially in urban areas where high customer density facilitates higher logistics effectiveness (Nemoto 1997; Boyer et al. 2009). Second, compared to traditional fleets of dedicated delivery drivers, CSL may provide an enticing means for recapturing value in the reverse supply chain or for quickly expanding capacity in response to unexpected demand surges as part of a mixed fleet. As transportation innovation often leads to associated advances in transportation modeling (Murray and Chu 2015), integrating crowdsourced logistics into fleet sizing and vehicle routing problems provides a first step toward finding the optimal fleet mix in a given market. Finally, a future research agenda is provided that can build upon the current findings to better inform how firms can leverage CSL to create customer value and benefit firm performance. The research potential for CSL is both tremendous and timely.

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Appendix – Figures and Tables

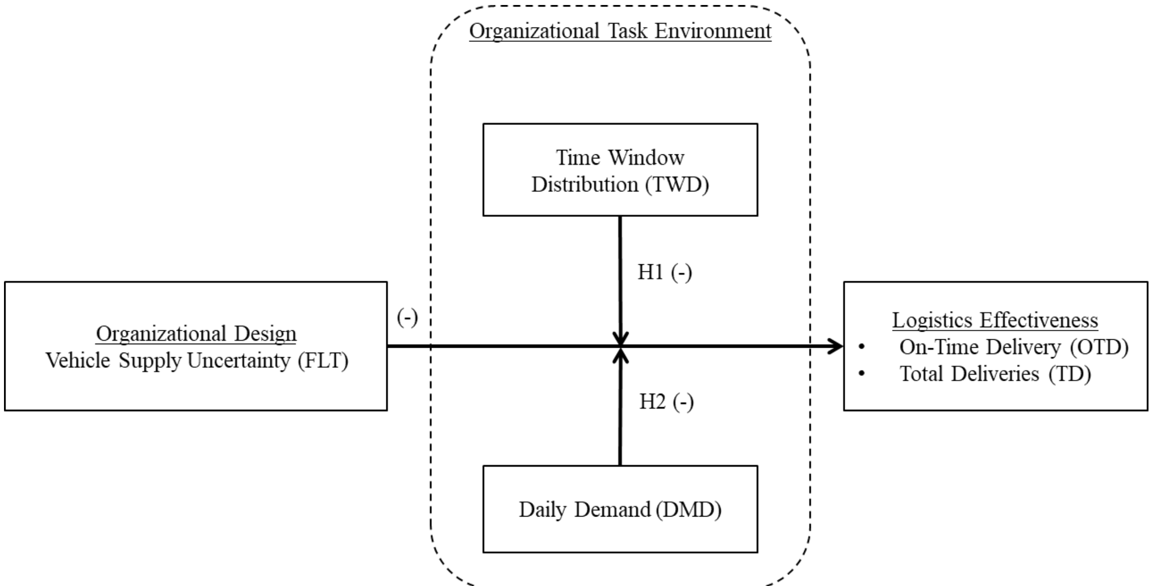

Figure 2 - Hypothesized Model

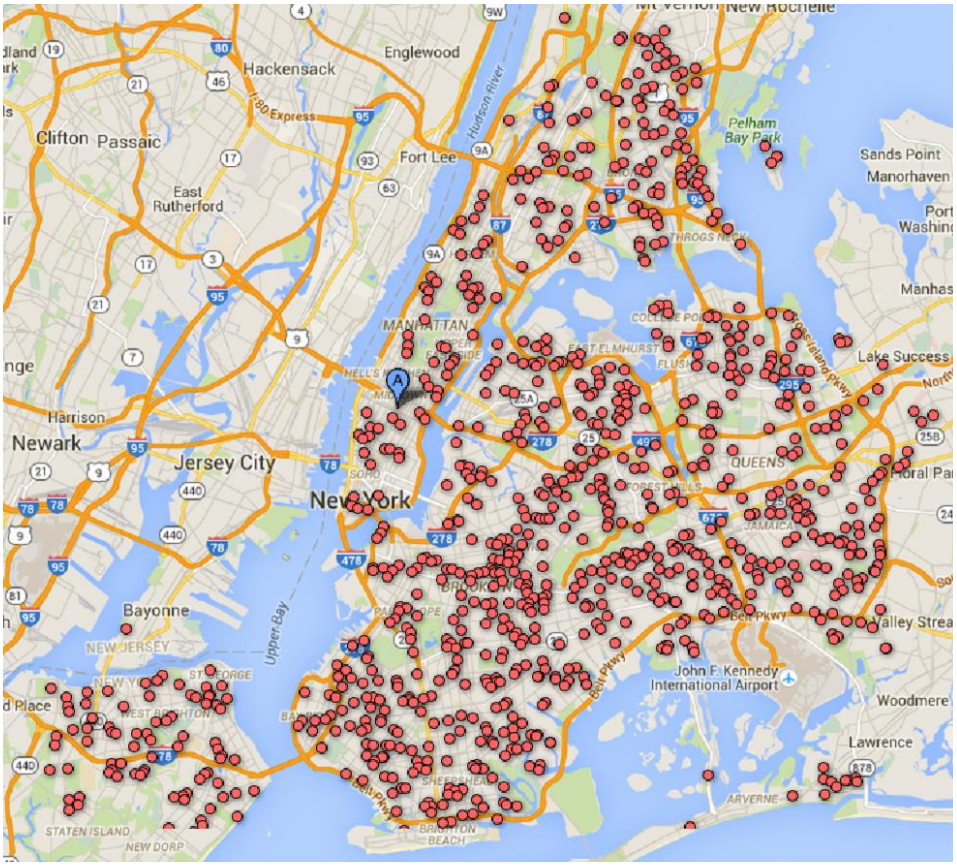

Figure 3 - Customer Network in NYC
Point “A” is Amazon’s Distribution Center in Manhattan. The red circles represent randomly chosen New York City residential and business addresses used in the study.

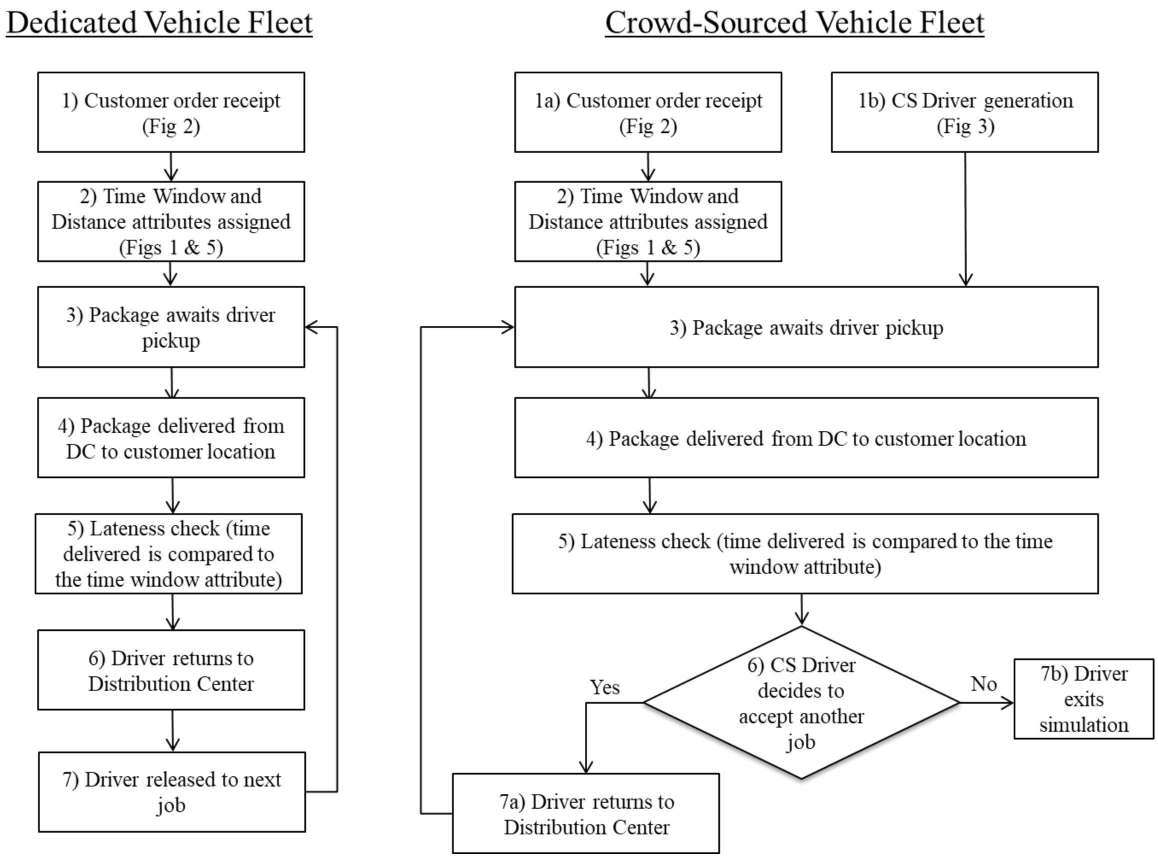

Figure 4 - Simulation Flow Charts

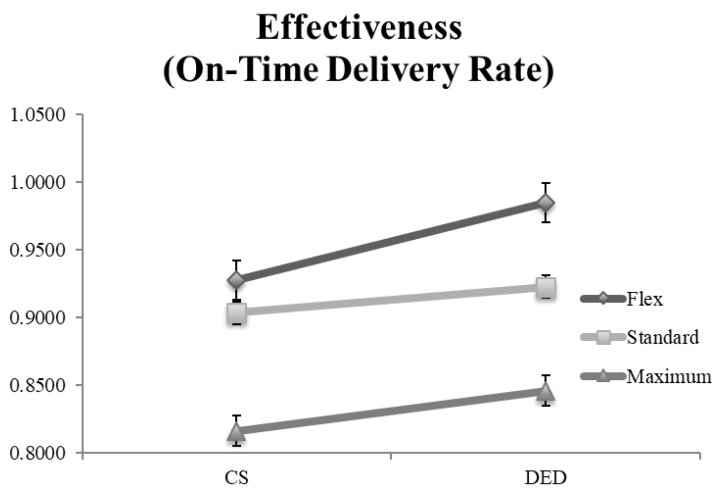

Figure 5a - FLTxTWD

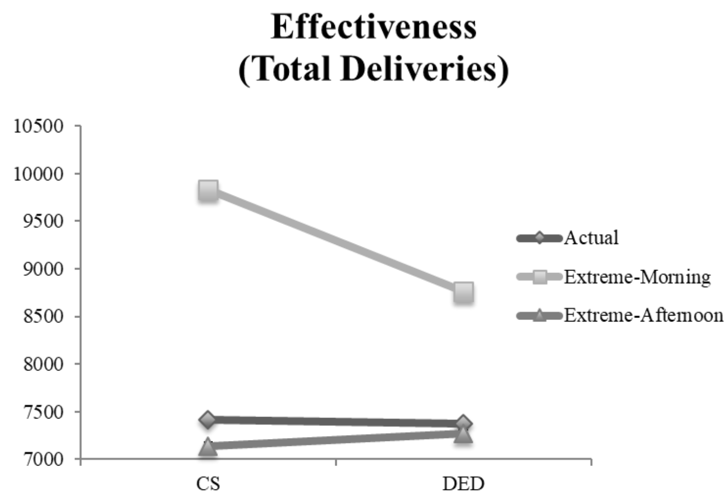

Figure 5b – FLTxDMD

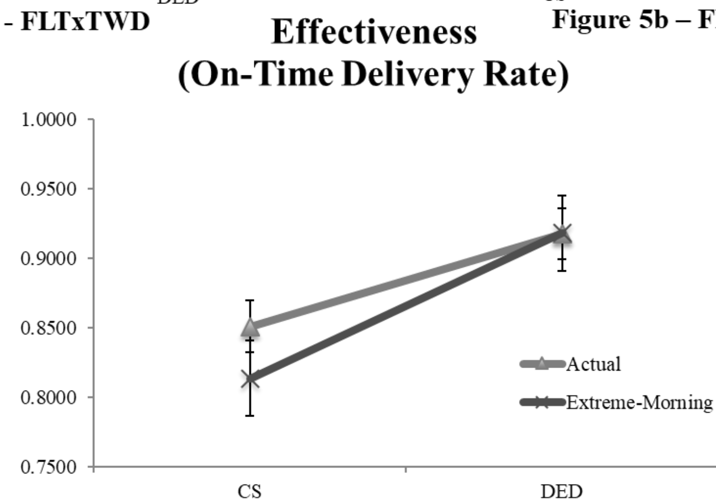

Figure 5c - FLTxDMD

Figure 5 - Significant Interaction Plots

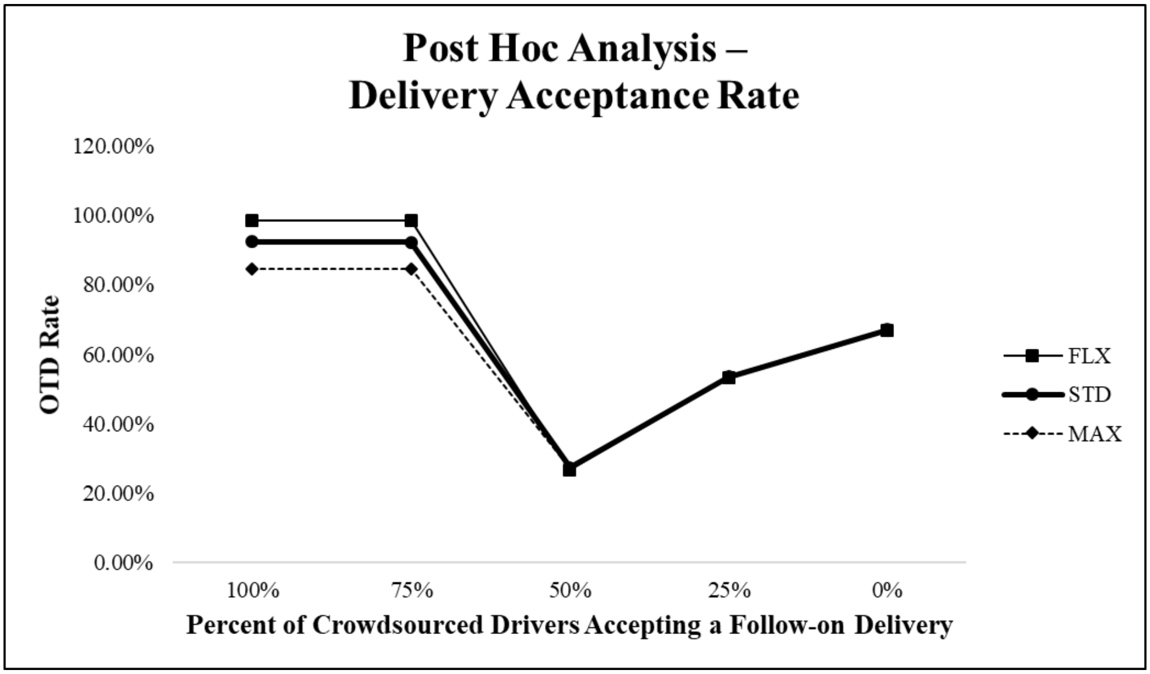

Figure 6 - Post Hoc Analysis - Delivery Acceptance Rate

Table 1 - Variable Definitions and Sources

Independent Variable	Definition	Measure	Source
Fleet Type (FLT)	CS fleets have uncertain availability throughout the day, whereas DED fleets have a constant number of drivers available throughout the day.	Binary: Crowdsourced (CS) or Dedicated (DED)	Availability of CS drivers is simulated by NYC Taxi supply data (NYC Taxi and Limousine Commission 2015). Poisson Intensity parameters, λ (drivers created per minute): (0.15, 0.18, 0.19, 0.20, 0.20, 0.22, 0.20, 0.18, 0.16, 0.13) Availability of DED drivers is constant and known.

Moderating Variable	Definition	Measure	Source
Time Window Distribution (TWD)	The combination of one-hour, two-hour, and four-hour time window requests for same day delivery services.	Three combinations of one-hour, two-hour, and four-hour delivery windows: Standard (STD), Flex (FLX), and Maximum (MAX)	Practitioner consultations (for STD and MAX profiles) Secondary data (for FLX profile)
Daily Demand Profile (DMD)	The arrival rates of orders throughout the workday follows one of five profiles.	Five profiles: Uniform, Low, Actual, Extreme-Morning, and Extreme-Afternoon Profiles	Low and Actual profiles adopted from Gendreau et al (2006) All other profiles from practitioner and subject- matter expert consultations

Table 1 Continued

Dependent Variable	**Definition**	**Measure**
On-time delivery rate (OTD)	A measure of logistics effectiveness indicating how many deliveries are made within the assigned time window relative to the total number of deliveries made	Number of on-time deliveries / total number of deliveries made
Total Deliveries made (TD)	A measure of logistics effectiveness indicating how many deliveries are made in each scenario	Total number of deliveries made

Table 2 - Descriptive Statistics

				Total Deliveries (TD)				On-Time Delivery Rate (OTD)			
				Crowdsourced		Dedicated		Crowdsourced		Dedicated	
Variable	**Profile**	**Probability Distribution (1hr-2hr-4hr time windows)**	**N***	**M****	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Time Window Distribution	Flex	10%-90%-0%	125	7615.13	1485.02	7413.74	1193.62	92.75%	8.20%	98.47%	0.13%
Time Window Distribution	Standard	50%-40%-10%	125	7615.94	1498.72	7420.86	1201.80	90.35%	4.58%	92.29%	0.32%
Time Window Distribution	Maximum	100%-0%-0%	125	7611.62	1492.68	7404.49	1192.37	81.64%	6.45%	84.61%	0.46%
Variable	**Profile**	**Poisson Intensity Parameters, λ (delivery requests per minute)**	**N***	**M****	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Daily Demand	Uniform	(0.55)	75	8354.88	97.30	8332.96	95.35	91.72%	5.70%	91.77%	5.73%
Daily Demand	Low	(0.75, 1.10, 0.25, 0.40, 0.10)	75	5320.79	73.97	5321.04	69.74	91.76%	5.72%	91.87%	5.67%
Daily Demand	Actual	(0.55, 0.70, 0.10, 0.40, 0.10)	75	7419.00	86.34	7378.72	104.39	85.10%	5.69%	91.76%	5.73%
Daily Demand	Extreme - Morning	(0.55, 0.75, 2.4, 0.25, 0.1)	75	9834.71	90.65	8759.35	39.28	81.38%	10.32%	91.79%	5.73%
Daily Demand	Extreme - Afternoon	(0.1, 2.4, 0.1)	75	7141.79	114.97	7273.08	111.60	91.28%	6.09%	91.77%	5.71%

**Number of observations for each cell*
***Mean and SD values per 30 workdays*

Table 3 - Results of Pairwise t-tests on the Equality of Means

		Total Deliveries (TD)				On-Time Delivery Rate (OTD)			
Source of Variation	**Profile**	**|Δ Mean|**	**t**	**df**	**95% CI of the Mean Difference**	**|Δ Mean|**	**t**	**df**	**95% CI of the Mean Difference**
Time Window Distribution X Fleet Type	Flex	201.39	-1.182	248	(-537.030, 134.246)	**5.72%**	**7.797**	**248**	**(4.27%, 7.16%)**
Time Window Distribution X Fleet Type	Standard	195.08	-1.135	248	(-533.503, 143.342)	**1.94%**	**4.712**	**248**	**(1.13%, 2.74%)**
Time Window Distribution X Fleet Type	Maximum	207.14	-1.212	248	(-543.690, 129.418)	**2.97%**	**5.146**	**248**	**(1.84%, 4.11%)**
Daily Demand X Fleet Type	Uniform	21.92	-1.393	148	(-53.005, 9.165)	0.06%	0.059	148	(-1.79%, 1.90%)
Daily Demand X Fleet Type	Low	0.25	0.022	148	(-22.945, 23.452)	0.10%	0.111	148	(-1.74%, 1.94%)
Daily Demand X Fleet Type	Actual	**40.28**	**2.575**	**148**	**(9.368, 71.192)**	**6.66%**	**7.142**	**148**	**(4.82%, 8.50%)**
Daily Demand X Fleet Type	Extreme - Morning	**1075.36**	**94.263**	**148**	**(1052.816, 1097.904)**	**10.42%**	**7.645**	**148**	**(7.72%, 13.11%)**
Daily Demand X Fleet Type	Extreme - Afternoon	**131.29**	**7.096**	**148**	**(94.732, 167.855)**	0.48%	0.500	148	(-1.42%, 2.39%)

Note: ***$p < 0.05$***

Table 4 - Results of Post Hoc Analysis Comparing CSL Driver Follow-up Delivery Acceptance Rates

Descriptive Statistics				**OTD**	
Fleet Type	**TWD Profile**	**Follow-up Job Acceptance Rate**	**N**	**M**	**SD**
Crowdsourced	Flex	75%	25	98.43%	0.13%
Crowdsourced	Standard	75%	25	92.24%	0.33%
Crowdsourced	Maximum	75%	25	84.53%	0.56%
Crowdsourced	Flex	25%	25	54.38%	1.48%
Crowdsourced	Standard	25%	25	53.78%	1.03%
Crowdsourced	Maximum	25%	25	53.53%	1.28%

Pairwise t-tests on the Equality of Means				**OTD**	
Source of Variation	**TWD Profile**	**|Δ Mean|**	**t**	**df**	**95% CI of the mean Difference**
Time Window Distribution	Flex	44.05%	**147.76**	**48**	**(43.45%, 44.65%)**
Time Window Distribution	Standard	38.46%	**178.34**	**48**	**(38.02%, 38.89%)**
Time Window Distribution	Maximum	31.00%	**111.25**	**48**	**(30.44%, 31.57%)**

Note: $\boldsymbol{p < 0.05}$*; This posthoc analysis compares the OTD of a crowdsourced fleet when drivers accept follow-up jobs at a rate of 75% with the case in which drivers only accept follow-up jobs 25% of the time.*

Table 5 - Future Research

Topic	Possible RQ(s)	Possible Method(s)
Crowdsourced and Dedicated Mixed Fleet Size Optimization	How can firms determine the optimal fleet mix for a combined crowdsourced and dedicated delivery fleet?	Optimization, Metaheuristics, System Dynamics Simulation
CSL for Reverse Logistics	How can CSL be leveraged to enhance reverse logistics?	Case Studies, Discrete Event Simulation
Crowdsourced Driver Supply Elasticity and Supply Management Strategies	What do crowdsourced driver supply elasticity curves look like and what affects them? What are the most effective crowdsourced driver supply management strategies?	Case Studies, Mathematical Modeling, Econometrics
Same-day Delivery Demand Management Strategies	How does crowdsourced logistics affect demand management strategies?	Experiments, Econometrics
The Suitability of CSL for Different Cities	How does CSL perform across various city types? How does traffic affect performance of CSL?	Simulation, Case Studies
Sharing Economy Business Models and Supply Chain Management	How does CSL compare to other sharing economy based models in the supply chain? How can they be leveraged to increase retailer performance?	Case Studies, Delphi Surveys
Brand Management and Customer Service Implications	How do consumers perceive the level of logistics service quality from a crowdsourced driver relative to other modes of transportation?	Grounded Theory, Experiments
Impact on Omnichannel Distribution Strategies	How does the use of CSL compare to traditional spoke-and-hub transportation modes for last mile logistics?	Case Studies, Agent-based Simulation
Motivations of Crowdsourced Drivers	How do crowdsourced drivers differ in terms of motivation? Why are some crowdsourced drivers more responsive than others?	Ethnography, Survey, Case Studies
CSL in B2B Contexts	How can CSL be best leveraged in B2B logistics?	Case Studies, Delphi Surveys

III. DESIGNING CROWDBASED LOGISTICS BUSINESS MODELS IN OMNICHANNEL DISTRIBUTION

Abstract

Retailers continue to seek agile logistics strategies and technologies for omnichannel supply chains. One such class of innovations emerges from the sharing economy where firms adapt crowdsourced business models for logistics and operations management. Understanding how this class of strategies and technologies, referred to as "Crowdbased Logistics Business Models," impacts value cocreation processes in an omnichannel supply chain provides insight into their potential impact on logistics strategy. Using a service dominant logic theoretical lens, this research applies a design science paradigm to explain why and how CLBMs can be expected to alter value cocreation processes. A multimethod study that pairs content analysis with expert Delphi panels is implemented to accomplish these tasks. Design propositions for the integration of CLBMs into omnichannel strategy are also made.

Introduction

The explosive growth of e-commerce has revealed an urgent need for increased agility and speed in retail logistics (Bell, Gallino, and Moreno 2014; Ta, Esper, and Hofer 2015; Hübner, Wollenburg, and Holzapfel 2016; Castillo, Bell, Rose, and Rodrigues 2017; Gallino, Moreno, and Stamatopoulos 2017; Gao and Su 2017; Letizia, Pourakbar, and Harrison 2018). In the US, effective and efficient order fulfillment for e-commerce is especially critical since it is currently the fastest growing retail channel (U.S. Census Bureau 2018); however, online customers have lower information seeking costs and greater retailer variety, so profit margins can often be slim. To improve fulfillment performance, many firms have developed omnichannel logistics strategies where inventory is consolidated and made available across channels, and fulfillment points are moved closer to demand markets within existing distribution networks (Brynjolfsson, Yu Jeffrey, and Rahman 2013; Bell et al. 2014; Ishfaq, Defee, Gibson, and Raja 2016; Gallino et al. 2017; Gao and Su 2017; Letizia et al. 2018). In doing so, many retailers have found that omnichannel logistics strategies result in faster fulfillment times and greater agility, which improve customer service quality and increase repeat purchases (Rabinovich and Bailey 2004; Rabinovich, Rungtusanatham, and Laseter 2008; Griffis, Rao, Goldsby, and Niranjan 2012), but may increase warehousing, distribution, and transportation costs (Ishfaq et al. 2016). Therefore, retail firms continue to seek innovative strategies and technologies to reduce the added logistics costs in an omnichannel strategy.

Some companies are experimenting with technology-based solutions such as drones or autonomous vehicles (Marchet, Melacini, Perotti, and Tappia 2013; Murray and Chu 2015). Others have developed novel logistics technologies and strategies inspired by the sharing economy (Savelsbergh and Van Woensel 2016; Carbone, Rouquet, and Roussat 2017; Castillo et al. 2017). For instance, Amazon Flex is the online retailer's adaptation of the Über or Lyft ridesharing business model known colloquially as Crowdsourced Logistics (CSL), which is dedicated to moving goods rather than people with independent contractors using their personal vehicles. Walmart has also explored an adaptation of crowdsourcing logistics capabilities referred to as "crowdshipping", where in-store shoppers or employees finishing a shift are compensated for delivering online orders to customers who reside nearby (Savelsbergh and Van Woensel 2016; Dayarian and Savelsbergh 2017). Both CSL and crowdshipping belong to a class of logistics strategies and technologies being developed in industry referred to henceforth as "Crowdbased Logistics Business Models" (CLBMs). CLBMs continue to evolve in the field but due to their nascence, it remains to be understood how they contribute value to organizations. Thus, CLBMs present an opportunity for Operations and Supply Chain Management (OSCM) scholars to conduct relevant, forward-looking research on their design and implementation (Van Mieghem 2013; Gallien, Graves, and Scheller-Wolf 2016; Toffel 2016; van Aken, Chandrasekaran, and Halman 2016; Anand and Gray 2017; Zinn and Goldsby 2017).

Accordingly, interest in crowdbased and sharing economy phenomena has risen greatly in recent years. The emergence and rapid growth of companies such as Flexe, which facilitates on-demand, short-term warehouse capacity sharing in a service akin to Airbnb, reflects increased practitioner interest and openness to how sharing economy-inspired business models can be integrated into logistics operations. Heightened academic interest in crowdbased phenomena in OSCM contexts has followed, with several novel research efforts being undertaken. Savelsbergh and Van Woensel (2016) analyze current trends in urban logistics and highlight the need for examining how crowdsourcing technologies provide dynamic delivery capabilities to retailers, a sentiment shared by Rose, Mollenkopf, Autry, and Bell (2016). Carbone et al. (2017) study a series of electronic platforms that facilitate logistics management via crowdsourcing and sharing economy business models while Castillo et al. (2017) simulate and examine the performance of a crowdsourced fleet of delivery drivers in New York City.

Empirical research on crowdbased operations and logistics phenomena continues to emerge. For instance, open innovation tournaments where new ideas and problem solutions are generated by the crowd have been studied by OSCM scholars to better understand their impact on a firm's innovation processes (e.g. Bayus 2013; Bockstedt, Druehl, and Mishra 2015; Ba and Nault 2017; Wooten and Ulrich 2017). Open innovation tournaments have so far proven to be a fruitful area of inquiry in crowdbased operations and logistics phenomena.

Another high-potential area of interest for OSCM empiricists to explore is how CLBMs are designed, how they are impacted by the contexts in which they're applied, and what the resulting outcomes are. Currently, this area of research is underexplored and to bridge this gap in the literature, a rigorous research strategy that can assess contextual information is needed (Stank et al. 2017). Design Science Research (DSR) offers such a perspective (Simon 1996; Pawson and Tilley 1997; van Aken et al. 2016). DSR seeks to develop knowledge "that can be used in an instrumental way to design and implement actions, processes or systems to achieve desired outcomes in practice" (van Aken et al. 2016, 1). The goal of the current research is to create relevant knowledge about value co-creation with CLBMs by applying a DSR paradigm to examine CLBMs currently being innovated in the field, how they're integrated into the value cocreation process in omnichannel logistics, and how CLBMs impact OSCM performance. To meet this goal, the following research question is asked: *Why and how do CLBMs impact omnichannel logistics and supply chain strategy?*

To explore this guiding research question, a multi-method study was undertaken that paired a content analysis of web-based archival data (Krippendorff 1980; Weber 1990; Tangpong 2011) with an expert panel of retail logistics executives and managers consulted through a Delphi process (Dalkey and Helmer 1963; Linstone and Turoff 2002; Okoli and Pawlowski 2004). Two important contributions are made to OSCM knowledge following this multi-method effort. First, a typology of CLBMs is developed, which provides a generic design for how firms can integrate certain CLBMs into omnichannel logistics strategy. This contribution also sheds light on the role of a novel, nontraditional socioeconomic actor in the value cocreation process: the crowd. To cocreate value with the crowd, firms must engage in "competitive collaboration" in which they develop recruitment and retainment techniques to compete with crowdmembers' alternative interests. Second, initial evidence of how the design may perform in certain contexts (i.e. pragmatic validity) is provided as well. The logistics experts provided perspectives on how they would expect five common CLBMs to perform with regards to OSCM measures and under three contexts: urban vs rural areas, same-day vs less-time sensitive deliveries, and high-value vs low-value products.

The remainder of the manuscript is organized as follows. A brief review of relevant literature is provided to understand how integrating CLBMs into logistics operations affects value cocreation processes. Next is an overview of the methodologies selected to help develop a generic design for integrating CLBMs into omnichannel strategy. This is followed by detailed accounts of Study 1 and Study 2, along with presentation of each study's results. Discussion of the results, design propositions, and implications for theory and management are presented. Finally, the limitations of the study, future research opportunities, and final conclusions of the research are given.

Relevant Literature Review

The literature review in design science research is intended to synthesize extant knowledge that can guide thought and insight into a managerially relevant problem (Van Aken and Romme 2012). The central problem for which the current research seeks to develop a generic solution is the integration of CLBMs into omnichannel strategy. To solve this problem, however, requires an understanding of how CLBMs affect value cocreation in omnichannel logistics. Thus, literature that can guide thinking about how crowdbased phenomena might impact those processes in omnichannel logistics was consulted. A brief overview of the service-dominant logic (SDL) perspective of value cocreation in omnichannel and crowdbased logistics is provided.

Service-Dominant Logic in Omnichannel Logistics.

Omnichannel logistics strategy is an evolution of multichannel distribution strategy where operations and logistics managers are expected to be able to fill orders received on a multitude of platforms, including mobile phones, websites, call centers, kiosks, or storefronts, from any inventory holding location (Agatz, Fleischmann, and van Nunen 2008; Bell et al. 2014). This means that in an omnichannel strategy, logistics managers view their inventory as a single mass of goods, rather than existing in distinct channels with little to no crossover (Hübner et al. 2016). In a multichannel strategy, an online order might only be filled from a single e-commerce distribution center, but in an omnichannel strategy, that same order would be filled from the nearest or most logical location, which could be a full-service distribution center or even a retail storefront (Gao and Su 2017).

The purpose then of omnichannel logistics is to increase agility and speed in serving increasingly stringent online customer expectations (Rigby 2011; Brynjolfsson et al. 2013). Stated differently, the purpose is to improve logistics customer service quality across all channels. Agility and speed are characteristics of a supply chain strategy that prioritizes responsiveness and improved logistics service quality (Gligor, Esmark, and Holcomb 2015). A firm adopting an omnichannel logistics strategy is then attempting to improve logistics service quality by increasing agility and speed (Rabinovich et al. 2008). Since the goal in omnichannel strategy is essentially to improve the firm’s service offering, it is reasonable to deduce that the firm is guided by a Service-Dominant Logic (SDL) (Vargo and Lusch 2004; Lusch 2011; Flint, Lusch, and Vargo 2014; Ketchen, Crook, and Craighead 2014; Stolze, Mollenkopf, and Flint 2016).

The SDL argues that firms don’t simply sell goods, rather, they provide services and make value propositions to customers (Vargo and Lusch 2004). At the core of SDL is the value cocreation process. Generally, value is collaboratively created between supply chain partners through “shared inventiveness, design, and other discretionary behaviors” (Ostrom et al. 2010, 24). SDL also argues that value cocreation is relational, taking place in a service ecosystem of socioeconomic actors over a period extending beyond the simple transaction (Vargo and Lusch 2004; Lusch 2011; Flint et al. 2014; Ketchen et al. 2014; Stolze et al. 2016).

Thus, value cocreation in omnichannel logistics can be understood to occur because of the relationship between socioeconomic actors tied together by a desire to increase supply chain agility and speed. The ecosystem of actors typically consists of a network of suppliers, buyers, logistics service providers, and customers, all of whom can be said to have strong relational ties among them (Granovetter 1973), since their relationships are typically formalized and contractual (Lusch 2011). However, when introducing the “crowd” as a new socioeconomic actor for providing logistics services, the delivery agent or warehouse space provider, for example, is not necessarily going to be the same person or company for every transaction. This means that CLBMs may introduce weaker relational ties to the service ecosystem and value cocreation process. To theorize about how introducing weaker relational ties with the crowd impacts value cocreation in the omnichannel supply chain ecosystem, recent research on crowdbased logistics and operations phenomena is reviewed.

Value Cocreation in Crowdbased Logistics and Operations Phenomena.

Most literature beginning to assess crowdbased phenomena in logistics operations takes an analytic perspective of the operation. For example, Arslan, Agatz, Kroon, and Zuidwijk (2016) and Archetti, Savelsbergh, and Speranza (2016) adapt the vehicle routing problem (VRP) to optimize delivery routes when the fleet consists of occasional drivers, as in the case of crowdsourced logistics (CSL). Wang et al. (2016) also optimize a pickup-point network design in an urban area when crowd members are compensated for making deliveries from the pickup-points to their destination. Similarly, Chen, Pan, Wang, and Zhong (2016) develop a system comprised of a fleet of taxi drivers who can be assigned to perform last mile deliveries when not providing rides. Other researchers have studied the ridesharing problem using analytic methods after the emergence of Uber (e.g. Agatz, Erera, Savelsbergh, and Wang 2011; Furuhata et al. 2013; Gargiulo et al. 2015; Lee and Savelsbergh 2015; McPhee, Paunonen, Ramji, and Bookbinder 2015; Stiglic, Agatz, Savelsbergh, and Gradisar 2015; Nourinejad and Roorda 2016; Stiglic, Agatz, Savelsbergh, and Gradisar 2016). Conducting analytical research on crowdbased logistics and operations phenomena helps to understand and improve the current systems being developed and how they're used in practice, but does not fully address the knowledge limitation in this emerging area.

Several OSCM scholars have also conducted empirical research on emergent crowdbased phenomena in operations and logistics contexts. For instance, the open innovation tournament, where firms seek to crowdsource new ideas or problem solutions, has received an increasing amount of attention. Ba and Nault (2017) call for understanding how the crowd is managed in these tournaments to improve innovation performance. They also describe the importance of studying the relational dynamic between the firm hosting the innovation tournament and the individual solution providers, a dynamic that is also present in CLBMs. Bayus (2013) found that if an individual crowd member's idea was adopted in one of these innovation tournaments, then additional ideas from that individual were likely to be similar to the original, in effect decreasing the diversity of ideas from that person over time. However, frequently providing feedback and respect to contributors throughout the process can improve the quality of the ideas received (Boons, Stam, and Barkema 2015; Wooten and Ulrich 2017). The idea generation process in an open innovation tournament is also impacted by crowd members' country of origin (Bockstedt et al. 2015), suggesting regional contexts play an important role in engaging with the crowd. What these research efforts have in common is the implication that when a firm engages with the crowd, *how* it chooses to do so can impact the intended outcomes. Thus, the context of the interaction makes a difference on the value cocreation process between a firm and the crowd.

Understanding the motivations of the crowd is important as well (Hossain and Kauranen 2015). In the case of ridesharing, driver motivations range from underemployment to a desire for expanded social networks (Anderson 2014;

Rosenblat 2016; Rosenblat and Stark 2016). An analogous range of motivations exists in CLBMs as well (Frehe, Mehmann, and Teuteberg 2017). When a firm sources from the crowd, it is forced to compete with individuals' other motivations to entice participation (Ndubisi, Ehret, and Wirtz 2016; Castillo et al. 2017). This means that cocreating value with the crowd requires "competitive collaboration," where the firm's compensatory offerings to the crowd must be more enticing than individuals' alternative interests.

This is a novel role for most companies since procurement of logistics service providers is typically based on the service level that can be provided, the overarching logistics strategy, and cost (Griffis, Goldsby, Cooper, and Closs 2007; Richey, Adams, and Dalela 2012). When using CLBMs, firms must implement recruiting and retainment activities as well, to ensure a steady supply of crowd members to provide the logistics service. Stated differently, when creating a "Business-to-Crowd" or B2Crowd relationship, competitive collaboration is the mechanism that alters the value cocreation process.

This brief literature review provides nascent theoretical insight into understanding why introducing CLBMs to omnichannel logistics changes how relevant value is co-created. To facilitate a successful B2Crowd relationship, firms should recognize they have to compete with individuals' alternative interests to collaborate for value cocreation and that the context in which a CLBM is applied likely makes a significant impact. With this insight into *why* the value cocreation process in omnichannel logistics is different, the next important issue is understanding *how* the integration of CLBMs into strategy can be designed to create relevant value.

Methodology

Because CLBMs are still being developed in practice and not yet widely studied in academia, an exploratory, multimethod approach was taken to gain insight from multiple perspectives on how they're used and how they can be expected to impact OSCM performance outcomes. A content analysis (Weber 1990; Krippendorff 2013; Neuendorf 2016) of archival data was paired with expert panels (Dalkey and Helmer 1963; Schmidt 1997; Linstone and Turoff 2002) consisting of experienced logistics professionals to develop and validate an initial typology of CLBMs. Content analysis was chosen for the initial theory development because it allows for analysis of a wide variety of qualitative content (Tangpong 2011). This includes white papers and publications from trade organizations (Rabinovich and Cheon 2011), which are the forms in which most information about CLBMs currently exists. But because a large amount of content covering CLBMs is sourced from practitioner publications and news outlets where the data may be subject to desirability bias (Tangpong 2011), there could be some concern about the validity of any results coming from only analyzing practitioner publications. To preemptively address this possible limitation and gain a deeper understanding of CLBMs, an expert panel was consulted through a Delphi process to enhance the validity of the findings from the content analysis by drawing upon the expertise of a group of senior logistics professionals with experience in transportation, omnichannel logistics, and retail supply chain management. The purpose of the Delphi process was to achieve consensus opinion among the panel of logistics experts about how to integrate CLBMs and how they can be expected to impact OSCM performance in terms of cost, quality, flexibility, innovation, and delivery (Krause, Pagell, and Curkovic 2001; Kroes and Ghosh 2010; Spring, Hughes, Mason, and McCaffrey 2017). After completing two rounds of the Delphi process, a nonparametric statistical analysis was then performed to assess the level of agreement among the panel experts with regards to CLBM design considerations and the expected OSCM performance impact (Skillings and Mack 1981).

Study 1 – Content Analysis of Web-Based Archival Data

Content Analysis Overview.

Content analysis (CA) is an empirical research method that allows for systematic classification and categorization of qualitative or textual data (Jick 1979; Flynn et al. 1990; Tangpong 2011). CA has been used in a variety of OSCM research efforts that, for example, analyzed corporate social responsibility and environmental reports to understand how firms approach sustainable supply chain management (Montabon, Sroufe, and Narasimhan 2007; Tate, Ellram, and Kirchoff 2010); studied archival website data to understand how regional logistics assets affect local economic development (Bolumole, Closs, and Rodammer 2015); and analyzed qualitative interviews to offer insight into how host government regulations affect logistics performance during humanitarian crises (Dube, Van der Vaart, Teunter, and Van Wassenhove 2016). CA is chosen for the first study in this research effort for two reasons: 1) it provides a basis for differentiating CLBM types, and 2) given the nascence of crowdbased phenomena in operations and logistics, written materials including white papers, press releases, and other news coverage involved in the development of these strategies provide the richest source of data for this study. The intended outcomes of the CA are twofold: 1) identification of CLBM applications, and 2) identification of the possible dimensions along which they vary. Both outcomes provide the starting point for developing questions for the expert panel participants in Study 2. The CA methodology is comprised of the following steps: identifying data sources, developing coding rules, analyzing the data, measuring interrater reliability, and reporting the results (Tangpong 2011; Krippendorff 2013; Neuendorf 2016).

Data Sources, Coding Procedure, and Analysis.

Textual materials found on supply chain-, logistics-, operations-, retail-, and technology-oriented websites and news organizations including white papers, presentations, interviews, and webinars yielded the data that were analyzed in this study. Data sources such as trade organizations, industry news outlets, and magazines have previously been identified as suitable for use in CA methodology in empirical OSCM research (Rabinovich and Cheon 2011; Tangpong 2011). Forty-seven documents or written items were obtained for coding by the research team, which is a quantity consistent with previous CA studies in OSCM (e.g. Montabon et al. 2007). The sources of these materials are presented in Table 6[2]. The materials were imported into QDA Miner 5.0 and manually coded for 1) identification of possible CLBMs, and 2) common and recurring themes which could be used to form the tentative dimensionality of the CLBM typology (Krippendorff 2013; Neuendorf 2016), which would then be refined in Study 2.

The coding procedure in CA methodology consists of identifying the recording unit, defining content categories, and establishing coding rules (Tangpong 2011). The recording unit in this study is a passage of text, which can be a sentence or paragraph that contains information relating to one of the two intended outcomes of the CA: 1) identification of a specific CLBM (e.g. crowdsourced logistics or asset sharing between companies) along with a description of what it is; and 2) themes addressing operational aspects of CLBMs such as how they can be implemented in logistics strategy or how they might differ from each other in terms of performance (that is, possible dimensionality).

Four content categories were identified in the coding process which provide the basis for forming the typology (see Table 7 for definitions): CLBMs, Strategy

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[2] All tables are provided in Appendix A for this chapter.

Integration, Performance Dimensions, and Concerns. These content categories emerged from the data by following a process of open, axial, and selective coding (Strauss and Corbin 1990) (see Table 7 for descriptions of coding rules as well).

Step 1. *Open coding phase*: a passage of text was selected as a recording unit if it was related to a concept in OSCM academic literature.

Step 2. *Axial coding phase*: similar recording units were grouped together to develop the content categories.

Step 3. *Selective coding phase*: the research team went back to the data sources and list of recording units to look for specific instances of each of the content categories. In this final step of the coding process, coding rules were established to ensure consistency in classifying recording units to the appropriate content categories.

Interrater Reliability Checks.

Based on the coding procedure adapted from previous OSCM research, 351 total recording units were extracted from the 47 source documents and assigned to one of four content categories based on the coding rules. Representative recording units for each content category are provided in Table 7. Two reliability coefficients were then calculated to ensure stability, reproducibility, and accuracy of results: Cohen's Kappa (Cohen 1960) and Krippendorf's Alpha (Krippendorff 2013). These coefficients measure interrater reliability by assessing chancecorrected observed agreement between raters (Weber 1990; Tangpong 2011). Both coefficients were calculated prior to resolving any disagreements among coders so that the results were not inflated. To calculate the coefficients, 10% of the recording units were randomly selected from the 351 total recording units and coded into the content categories by an independent analyst not associated with the project to compare with the research team's results. Cohen's κ and Krippendorf's α were then calculated using R and SPSS 24, respectively. Both coefficients (κ = 0.71, α = 0.72) were above the recommended 0.70 threshold (Tangpong 2011; Neuendorf 2016), thus the information from the CA was deemed to be sufficiently reliable.

Content Analysis Results.

Seven CLBMs were identified, as described in Table 8: Crowdsourced Logistics (CSL), Crowdshipping, Bicycle Messengers, Click-and-Collect, Pickup Point Networks (PPN), "Über-for-Trucking", and Logistics Asset Sharing. Based on the information found in the source documents, these seven CLBMs can be differentiated by the tier of the supply chain in which they're found; that is, in a Business-to-Business (B2B) tier somewhere in the supply chain upstream of the final mile, or in the Business-to-Consumer (B2C) tier in the last mile of the supply chain. Additionally, the CLBMs that are used for last mile fulfillment can be further separated into Product-to-Consumer (P2C) and Consumer-to-Product (C2P) categories as well (Savelsbergh and Van Woensel 2016). Examples of companies that have adopted these CLBMs or platforms that facilitate usage of CLBMs between a shipper and a customer are also provided in Table 8.

The second outcome of the CA emerged from the open, axial, and selective coding process. The coding process resulted in three major themes to provide an initial foundation for the CLBM typology framework. These themes were used as the content categories which address three aspects of CLBMs: 1) how they are integrated into omnichannel strategy (Strategy Integration); 2) their expected impact on OSCM performance (Performance Dimensions); and 3) any obstacles to implementation or significant risks associated with them (Concerns).

The content categories provide tentative design considerations of the CLBMs. The Strategy Integration category contains recording units that address how a shipper can integrate a CLBM into its logistics and supply chain operations. Specifically, Industries, Supply Chain Tiers, and Geographic Regions were identified in the coding process as the items that can provide one set of initial dimensions for differentiating CLBMs. The Performance Dimensions category contains recording units that discuss how a CLBM may result in improved economic and logistics or operational performance. Specifically, the tentative dimensions within this category are Logistics Performance (Effectiveness and Efficiency), Operational Performance (Cost, Quality, Flexibility, Innovation, and/or Delivery), and Economic/Financial Performance. Lastly, the Concerns content category consists of Risk Mitigation and Regulatory Issues.

Study 2 – Consulting with Logistics Expert Panels through Delphi Process

Overview of the Delphi Process.

The Delphi method is a research technique that seeks to achieve consensus opinion on a topic by a panel of experts (Dalkey and Helmer 1963; Schmidt 1997; Linstone and Turoff 2002; Okoli and Pawlowski 2004; Seuring and Müller 2008; Bolumole et al. 2015; Richardson, de Leeuw, and Dullaert 2016). The Delphi process consists of structured communication among members of the expert panel that allows the group to collectively address a complex issue (Dalkey and Helmer 1963; Linstone and Turoff 2002). The communication structure typically involves experts responding to a series of questionnaires that facilitate interaction in a controlled manner. The strength of the Delphi method lies in its ability to resolve differences in opinion among a group of experts (Schmidt 1997). Thus, it was selected for the current research because it can enable exploration of nascent phenomena, such as CLBMs, in which little empirical data exists but a plethora of opinions abound about their utility and design. Furthermore, the level of agreement between experts in the Delphi process can be tested using nonparametric statistical methods (Schmidt 1997; Okoli and Pawlowski 2004; Hollander, Wolfe, and Chicken 2014), thus enhancing the rigor of the Delphi process relative to other qualitative methods. The Delphi process for the current research consisted of selecting experts, determining the number of polls to ask the expert panel, determining the content of questionnaires, analyzing the responses, and assessing the level of agreement among the experts.

Expert Selection.

Experts were recruited from three sources: 1) a practitioner conference about e-commerce, retail supply chain management, and last mile logistics operations; 2) a university forum of practitioner organizations with a focus on logistics and supply chain management; and 3) online professional forums that focus on last mile logistics and omnichannel supply chain management. The research team contacted individuals through these sources and invited them to participate in the panels if they were deemed to have sufficient experience and knowledge of e-commerce, retail supply chain management, omnichannel logistics, and/or transportation operations. A total of 35 experts were recruited to participate in the first round of the Delphi process and 18 were recruited for the second round. While there is some variation in the literature regarding recommended Delphi panel size, these numbers are consistent with previous studies that suggest between ten and twenty participants are needed (Okoli and Pawlowski 2004; Richardson et al. 2016). The demographics for the panels are reported in Table 9.

Number of Delphi Rounds, Questionnaire Content, and Data Analysis Overview.

The Delphi process ideally continues until the experts make no further insights about the phenomena under investigation (Seuring and Müller 2008). In practice however, panel members have limited time windows in which researchers can entice participation. Therefore, the number of questionnaires was limited to two rounds, as in prior Delphi studies (e.g. Bolumole et al. 2015).

The questionnaires were designed to facilitate a process of brainstorming, consolidation, and evaluation among the experts (Okoli and Pawlowski 2004; Seuring and Müller 2008). The first round facilitated brainstorming by asking open-ended questions about designing CLBMs (see Appendix B for questionnaire). The responses were then content analyzed using a coding approach similar to the one used in Study 1. The research team then consolidated the first-round results to create the second-round questionnaire (see Appendix B) in which the experts were asked to provide more in-depth opinions and evaluations on three design-related topics: 1) expected impact of various CLBMs on traditional OSCM performance measures, 2) consolidation of the broad list of design considerations (concerns and risks) from the Round 1 questionnaire, and 3) ranking of those design considerations in order of importance. The Skillings-Mack (SM) test was then performed to assess the level of agreement among the experts on the expected performance impact of each CLBM along with the most pertinent associated risks (Skillings and Mack 1981).

Round 1 Results: Identifying CLBMs and Design Considerations.

The first round of the Delphi process consisted of general, open-ended questions about CLBMs. The purpose of the first round was to validate findings from the content analysis in Study 1 and to ask for opinions about designing CLBMs. Specifically, the experts were asked which CLBMs are being innovated in their industry or which ones could potentially work in their industry given the list of seven CLBMs from Study 1. Additionally, the experts were asked who the main actors in a CLBM are (e.g., a shipper, customer, and member of the crowd as a delivery agent), the contexts in which CLBMs are most likely to be successful (e.g., geographic regions, industries, or product segments), and what concerns or risks would have to be resolved prior to implementing a CLBM (i.e., the "design considerations"). These brainstorming type questions resulted in a qualitative data set of 35 responses to the four open-ended questions.

The set of responses were content analyzed iteratively. First, all responses were coded in an open and selective manner. The intent was to select mentions of the seven CLBMs from Study 1 (which were used as the content categories), while also remaining open to mentions of new CLBMs. Four new crowdbased business models or strategies, not previously identified in the content analysis, were identified in the Delphi panel (see Table 5); however, only one of the new four can be considered directly applicable for logistics management. The other three business models are for procuring office staff, sharing office space, and procuring knowledge-based services. The new list of eight CLBMs and the three non-logistics business models are provided in Table 10 along with the counts for each.

The second step in analyzing the first Delphi questionnaire consisted of open coding the dataset again to identify two types of design considerations: the contexts in which CLBMs are likely to be successful and the concerns or risks needing to be resolved prior to implementation. Examining the dataset for contextual variables that the experts suggested would be conducive to using a CLBM was the first step. Codes that were similar to each other in terms of how CLBMs could be used (i.e. contexts) were grouped together to form a collection of themes. For example, sixteen experts suggested that one of the seven CLBMs would likely be successful in urban regions, whereas five described scenarios in which a CLBM could be used in rural areas. These 21 recording units were tentatively identified as being part of a *"Population Density"* theme, or contextual variable that would enable success (see Table 5). This contextual variable was identified as tentatively having two dimensions, *"Urban Areas"* and *"Rural Areas."* In addition to *Population Density,* two other contextual variables were identified along with provisional dimensionality: *Urgency of Delivery* (with dimensions of *Same-day Delivery* and *Time-insensitive Delivery*), and *Product Characteristics* (with *High-value* and *Low-value* dimensions). These three items were the only ones that emerged from the data that revealed any sort of theoretical tension among the experts as to when CLBMs are likely to be successful or not, making these three items the most important to address in the subsequent Delphi questionnaire.

With regards to concerns or risks involved with implementing CLBMs, after the open coding process was completed, similar recording units were grouped into 7 new themes (reported in Table 5): *Liability & Insurance* (who bears financial responsibility for adverse events?), *Customer Experience* (how do CLBMs impact the customer experience?), *Operational Issues* (how is the CLBM integrated into current operations or how is it managed day-to-day?), *Regulatory Issues* (e.g., does the government consider the delivery agents to be employees or contractors?), *Employee/Contractor Reliability & Performance* (personnel screening, training, and performance monitoring), *Economic Sustainability of the CLBM* (what is the revenue model and does it pay for itself?), *IT Integration* (how well does the platform integration with current supply chain IT systems?), *Governance and Agency Issues* (how is the B2Crowd or B2B relationship governed?) and *Protecting the Shipper's Brand* (how is the shipper's reputation impacted by the CLBM?). To determine if these design considerations can be expected to vary in importance depending on the CLBM being implemented, the experts were asked in the second round to evaluate the list of concerns and rank them in order of importance to facilitate the development of generic CLBM design propositions.

Round 2 Results: Ranking CLBM Performance Impacts and Design Considerations.

The research team consolidated findings from the first round to hone the focus of the second questionnaire. While there was a list of eight CLBMs (and three non-logistics business models) generated from Study 1 and the first Delphi round, only the top five CLBMs were selected to be studied in the second round. This decision was made primarily to reduce the length of the second questionnaire. Additionally, only the top five CLBMs had more than one expert comment on it, with the exception of *crowdshipping*, which is the recruitment of in-store shoppers to make deliveries to online customers on behalf of the retailer (Dayarian and Savelsbergh 2017). The research team ultimately removed *crowdshipping* from the second Delphi round because Walmart was the only company found to be developing this particular CLBM and no evidence could be found that it achieved widespread adoption or implementation beyond the testing phase. Thus, it was decided that significant insight would not be lost by omitting this CLBM from the final Delphi panel.

In the second panel, experts were asked a series of questions about the five most commonly mentioned CLBMs from the first round. These questions were intended to assess the panelists' opinions regarding the expected impact on OSCM performance factors of each CLBM and the concerns or risks associated with each. The performance-related questions obtained the experts' opinions on what they would expect the impact of each CLBM to be on Cost, Quality, Innovation, Flexibility, and Delivery performance, where Delivery was separated into multiple sub-measures to examine the *Population Density*, *Urgency of Delivery*, and *Product Characteristics* contextual variables from the first Delphi round (see Appendix B for the complete questionnaire). For each CLBM, the experts were asked if they expected each performance dimension to increase or decrease on a sliding 7-point Likert scale (a score of 1 means they would expect it to 'Decrease' under the CBLM and 7 means they would expect it to 'Increase'). The results are listed in Table 11.

The questionnaire also included three attention checks where the expert was asked to move the slider to a certain value (Abbey and Meloy 2017). Three sets of responses were eliminated in the second round as a result of failing these attention checks, leaving a panel size of 15 useable questionnaires with improved data quality. After calculating the descriptive statistics for all performance measures, the expected performance impact data were converted to a ranked dataset in order to assess the level of agreement among experts as to how each OSCM performance factor would be impacted by each CLBM. The purpose of converting to a ranked dataset was to be able to use a nonparametric statistical method to evaluate the level of agreement among the experts.

With regards to the design considerations (i.e. concerns and risks) of CLBMs, the panelists were asked to choose the top four most important concerns from the larger list and then rank those four in order of importance from 1-4 (with 1 being the most important). This step allowed the research team to also assess the level of agreement among the experts using nonparametric statistics. The output of this step was a ranked dataset for each CLBM consisting of the four most important concerns to address prior to implementing a CLBM into its logistics strategy; any items not receiving a rank of 1-4 were given a rank of 5 *a posteriori*, indicating they were less important to that expert than the ones selected. This meant that the ranking dataset included ties. Additionally, not all of the concerns identified in Delphi round 1 were applicable to all CLBMs; for example, “Contractor Screening” is a concern for using crowdsourced logistics (CSL) because the delivery agent is a contractor and not necessarily an experienced professional. However, in the case of PPNs, there is no contractor because the consumer picks up the parcel on their own from a secured location. Thus, “Contractor Screening” was removed from the questionnaire for PPNs. The research team reviewed the applicability of each design consideration to all five CLBMs and removed those that weren’t relevant, resulting in an unbalanced design.

Between assigning a lower rank to the concerns not selected as one of the top four and eliminating certain concerns from the questionnaire when they weren’t relevant, an unbalanced ranked dataset with ties remained to be analyzed. Thus, a statistical method that could handle such a dataset to assess the level of agreement among the experts was needed. Kendall’s coefficient of concordance (*W*) is the most commonly used nonparametric statistical test used for testing level of agreement among judges (Schmidt 1997; Okoli and Pawlowski

2004). However, calculation and interpretation of Kendall’s *W* becomes convoluted when the ranked data includes ties (Schmidt 1997). Furthermore, because not all questions were asked for each CLBM (that is, there is missing data), the dataset was unbalanced, which violates a condition for calculating Kendall’s *W* (Kendall and Gibbons 1990). Therefore, the Skillings-Mack test (Skillings and Mack 1981), which ably handles ties in ranking data and unbalanced panels (Hollander et al. 2014), was performed to assess the level of agreement among experts with regards to the most important CLBM concerns and risks.

The Skillings-Mack (SM) test is a generalized version of Friedman’s (1937) test for differences between treatments in a randomized block design when data violate normality assumptions, as in the case of ranked data. Generally, the null hypothesis in the SM test is that no differences exist between treatments and is rejected when the observed SM statistic is greater than the critical SM statistic. The critical SM statistic is typically derived from the χ^2 distribution at a level of 5% significance and $k - 1$ degrees of freedom (Skillings and Mack 1981; Hollander et al. 2014). However, when sample sizes are small, the χ^2 distribution is inadequate and conservative (Skillings and Mack 1981; Chatfield and Mander 2009). Therefore, when small sample sizes are present, as in the current study, the critical SM statistic should be derived from the total number of rank configurations and pattern of missing observations using Monte Carlo simulation (Skillings and Mack 1981; Chatfield and Mander 2009). In the Monte Carlo simulation, the distribution of SM statistics under the missing observations pattern is calculated, which provides the critical SM. Then, the p-value of the difference between the critical and observed SM statistics is calculated by comparing the number of times the simulated SM statistic exceeds the observed SM statistic divided by the number of simulations performed (Hollander et al. 2014). The observed and critical SM statistics were calculated using R (Srisuradetchai 2015; Schneider, Chicken, and Becvarik 2017).

When assessing experts' expected impact on OSCM performance factors and opinions on the most important design considerations for each CLBM, the null hypothesis for each CLBM that no differences exist in opinion was rejected. That is, for each CLBM, the judges reached consensus that a certain performance impact could be expected to occur and that some design considerations are more important than others. The null hypotheses were rejected at the 5% level of significance (see Tables 12-13 for results).

Results for CSL.

Calculating the weighted sums of centered ranks for each design consideration indicates the experts' consensus on the highest and lowest ranked observations (Chatfield and Mander 2009). The magnitude of the weighted sum of centered ranks reflects the level of agreement between the judges and the sign indicates high or low rankings (Chatfield and Mander 2009). Thus, a large, negative weighted sum of centered ranks indicates consensus around a ranking of 1. For instance, the experts generally agree that the expected impact on the *Cost* (-29.77) performance factor has a ranking of 1 for CSL, meaning that more judges agree that it would reduce *cost* (a rank of 1 corresponded with an expected "decrease" in that factor on the questionnaire). This is the highest magnitude of the adjusted sums for CSL so there is the most agreement about the expected impact on *cost* than there is about the other OSCM performance factors (see Table 12). *Quality* (-24.02) also received a consensus low ranking from the experts but this indicates that the expected logistics service quality would be reduced when using CSL. This consensus negative view was also found for the *Ability to Deliver in Rural Areas* (-24.02) and the *Ability to Delivery High-Value Products* (-19.32) when using CSL. Conversely, the experts felt that using CSL would increase *Flexibility* (22.98) and the *Ability to Provide Same-Day Delivery* (32.90). Additionally, the experts agreed that *Operational Issues* (-30.67), *Customer Experience* (-24.10), and *Liability & Insurance* (-6.57) were the three most important design considerations for CSL, respectively. However, the relatively small magnitude on *Liability & Insurance* suggests there is not as much agreement as the former two considerations (see Table 13).

Results for Electronic Marketplaces.

The experts shared consensus that when using an electronic marketplace to procure long haul transportation services (i.e. Über for Trucking), *Cost* (-21.93), *Quality* (-16.19), and the *Ability to Delivery High-Value Products* (-17.76) would be reduced. They agreed however that *Flexibility* (31.86), *Innovation* (17.23), and the *Ability to Deliver in Urban Areas* (13.06) would increase. With regards to the design considerations, *Customer Experience* (-28.29) and *Operational Issues* (-15.01) were found to have the greatest consensus among the experts as being the most important issues to address first.

Results for B2B Asset Sharing.

When potentially using an electronic platform to share logistics assets, such as warehouse space, the experts generally agreed that *Cost* (-32.38), *Quality* (-26.11), and the *Ability to Delivery High-Value Products* (-16.71) would all decrease while *Flexibility* (27.68), *Innovation* (22.46), and the *Ability to Provide Same-Day Delivery* (16.19) would all increase. The experts also agreed that *Operational Issues* (-34.29) was the most important design consideration to resolve prior to adopting a logistics asset sharing service.

Results for BOPIS.

Strong agreement was found that BOPIS could result in a decrease in *Cost* (-41.96). In fact, this opinion had the strongest consensus of all OSCM performance factors proposed. *Flexibility* (-12.46) is expected to decrease however, which is the only CLBM in which the experts agreed *Flexibility* would decrease rather than increase. The experts are in agreement that the *Ability to Provide Same-Day Delivery* (21.62) and the *Ability to Delivery High-Value*

Products (21.93) would increase under BOPIS. There is nearly the same magnitude of agreement between an expected increase in the *Ability to Deliver to Urban Areas* (11.04) and an expected decrease in the *Ability to Deliver to Rural Areas* (-11.67), showing there is some controversy as to the *Population Density* contextual variable. The most important design considerations were agreed to be the *Customer Experience* (-26.94) and *Operational Issues* (-26.94).

Results for PPNs.

Finally, the experts achieved a level of consensus about an expected decrease in *Cost* (-31.86) and *Ability to Delivery High-Value Products* (-16.19) when using a PPN. They also strongly agree on an expected increase in the *Ability to Deliver to Urban Areas* (27.16) and the *Ability to Provide Non-Time Sensitive Delivery* (24.02). *Operational Issues* (-16.97) was found to have the most agreement as being the most important design consideration when implementing a PPN.

Discussion

This design science effort has yielded insight into the problem of how sharing economy inspired business models can be used to improve operations and supply chain management (OSCM) strategies. Study 1 consisted of content analyzing textual documents for specific examples of how the class of Crowdbased Logistics Business Models (CLBMs) are used in practice, insight into how they differ from each other, and how they impact OSCM strategy. The result was an initial typology that can be used to classify CLBMs based on the tier of the supply chain in which they're applicable, the movement direction of the package for those CLBMs used in the last mile, and the type of relationship that governs the CLBM. The former two classification criteria (relevant supply chain tier and movement direction) are also found in previous research (e.g. Savelsbergh and Van Woensel 2016). However, the latter classification criteria include a new type of relationship beginning to emerge in academic literature: the B2Crowd relationship where firms "competitively collaborate" with the crowd to procure business-related services. The B2Crowd relationship challenges firms' perceptions of the traditional role of a business because they are forced to compete with individuals' other interests to entice participation in the value creation process (Rosenblat and Stark 2016; Castillo et al. 2017).

The purpose of Study 2 was to more deeply explore how CLBMs may perform in certain contexts and what design factors have to be accounted for prior to implementation. To accomplish this goal, a group of logistics experts provided opinions on how five CLBMs could be expected to perform in terms of Cost, Quality, Innovation, Flexibility, and Delivery (Krause et al. 2001; Kroes and Ghosh 2010; Spring et al. 2017). Additionally, the group provided opinions on determining the most important CLBM design considerations. For both tasks, the level of consensus among the judges was then assessed statistically using a nonparametric method.

Expected Impacts of CLBMs on OSCM Performance.

Overall, the experts generally agreed that as a whole, CLBMs may reduce costs, increase flexibility, and increase innovation. This aligns with previous research on crowd logistics suggesting the sharing economy may offer a means of reducing OSCM costs (Carbone et al. 2017) and increasing agility in the supply chain's last mile (Castillo et al. 2017). However, the experts also strongly agreed that such improvements could be offset by reduced logistics service quality, since the crowd is comprised of amateurs and may not have the same level of professionalism as regular delivery agents (Carbone et al. 2017). Additionally, the experts suggested, although with a lesser degree of consensus, there would be reduced ability to deliver in certain contexts. Specifically, CLBMs are likely more appropriate for delivery in urban areas than rural ones and are likely not suitable for delivering high-value products to customers. The general feeling among the experts that CLBMs may not be feasible for rural areas is somewhat unexpected, as previous research argues that crowd logistics may be useful in underserved markets where distribution networks are under developed (Carbone et al. 2017).

There is some nuance in these general findings however that requires expatiation. Some opinions about the performance impact of BOPIS tended to run counter to the rest of the CLBMs. In particular, there was agreement that flexibility may be reduced under BOPIS, which is unexpected because it should provide another channel to deliver relevant value to the end customer. However, in practice, not all SKUs are eligible for BOPIS because it may reduce foot traffic in store where customers tend to be more profitable (Gao and Su 2017). Thus, while BOPIS creates a new delivery channel, it’s only for certain products which then have to be picked by in-store employees, which creates new constraints. Additionally, there was agreement that BOPIS was not suitable for serving rural areas, which could reflect a feeling that customers in those regions would essentially become penalized for not living within a short distance of the retail store. BOPIS was also the lone exception to the expected impact on the ability to deliver high value products in that it was expected to increase this ability. This is because keeping the goods in-store provides an increased level of security needed to mitigate risk of damage or shrinkage (Gao and Su 2017). Of all the opinions provided in the study, the strongest consensus was that BOPIS would provide a reduction in cost, which is the result of not having last mile transportation costs, in effect, turning the end customer into their own delivery agent.

Finally, there was a consensus that some CLBMs (CSL, Logistics Asset Sharing, and BOPIS) would be able to improve the ability to provide same-day deliveries. However, in the case of using CSL for same day delivery, an effective remuneration schedule has to be in place to mitigate risks associated with an uncertain supply of delivery drivers (Castillo et al. 2017). The experts also agreed that CSL and PPNs would improve delivery capabilities when shipments are less urgent (2 days or more).

CLBM Design Considerations.

As a whole, the most important CLBM design considerations for the experts were *Operational Issues* and the *Customer Experience*. These two factors had the strongest degree of consensus and the highest rankings. It is not entirely unexpected that *Operational Issues*, such as how to integrate a CLBM into current operations or how manage it day-to-day, was the most important design consideration since CLBMs are nascent, evolving, and might not be thoroughly understood yet. Additionally, many retail logisticians maintain a primary focus on creating relevant customer value (Stank, Esper, Crook, and Autry 2012); therefore, it is also not unexpected that *Customer Experience* was found to be highly important. On the other hand, *Regulatory Issues* was consistently ranked as a lower importance design consideration. Given the history of regulatory conflicts over whether crowdsourced drivers are employees or contractors of a firm, it would have been reasonable to expect higher consensus on the importance of this risk factor. However, this may just reflect that fact that since regulations are continuing to evolve, the socioeconomic actors in the omnichannel service ecosystem are more concerned with operational aspects of CLBMs.

Design Propositions & Pragmatic Validity.

Design propositions offer guidance on how and where a generic design can be used in the field and are a core aspect of a design science research effort (van Aken et al. 2016). The findings of the two studies undertaken in the current research can provide the basis for generic design propositions in the adoption and implementation of CLBMs into logistics and supply chain strategy. The following design propositions are made for companies considering their use:

1. Integrate CLBMs into densely populated customer networks (i.e. urban areas);
2. CLBMs should be used to provide low-value goods primarily, except for the case of BOPIS;
3. Know which CLBMs are better suited to providing same-day delivery services and which are more appropriate for standard or non-urgent deliveries.

Before these three design propositions can be trusted, discussion of their pragmatic validity is warranted. Pragmatic validity refers to whether or not a design will work after contextualization and implementation (van Aken et al. 2016). It can be achieved in a multitude of ways, including full field testing, pilot testing, or can be demonstrated through conversations with focus groups comprised of experts (van Aken et al. 2016) (van Aken et al. 2016). Due to the nascence of the CLBM phenomena and limited prevalence of managers and executives with direct experience using CLBMs, any type of field testing would not have been feasible in this study. Instead, a panel of logistics experts was consulted through a Delphi process to elicit consensus agreement about the potential impacts on OSCM performance outcomes of five types of CLBMs. This collaboration about the potential performance outcomes with the experts shows acceptable pragmatic validity in the generic design of CLBMs developed in this article (Dresch, Lacerda, and Antunes 2015).

Theoretical & Managerial Implications.

Two important theoretical implications are made in this research effort. First, a typology of CLBMs is developed. This typology forms a generic design for how certain CLBMs can be integrated into omnichannel logistics strategy, for which design propositions are made. The role of the crowd as a novel, nontraditional socioeconomic actor in the value cocreation process is explained as well. Second, initial evidence of the generic design's possible outcomes (i.e. pragmatic validity) is provided as well. The experts provided opinions on how they would anticipate five common CLBMs to affect OSCM measures in general and under three contexts: urban vs rural areas, same-day vs less-time sensitive deliveries, and high-value vs low-value products. Managerially, firms considering implementing crowdbased strategies in their supply chains can benefit from the generic designs. The research effort identifies contexts in which CLBMs are most likely to be successful in terms of population density, urgency of delivery, and product characteristics. Finally, a collection of design considerations that need to be made when employing CLBMs were identified.

Limitations and Future Research.

There are limitations to this study as well. Content analysis is constrained by the fact that only existing textual documents can be analyzed. There is likely important information not yet available in written form, thus there is a possibility that the current study has missed pertinent information. This possibility was mitigated through collection of primary data through the use of the Delphi panel, which also serves to strengthen validity of the findings. Additionally, only three contextual variables were identified in the research process – population density, delivery urgency, and product characteristics. There are likely more contexts that should be considered and explored in future research. Another limitation is that experts were asked what they would expect the performance impacts to be, which is different from asking what they are. The latter implies that the participants have sufficient direct experience with CLBMs but due to CLBM nascence and lack of widespread adoption in the field, seeking consensus opinion on the design and outcomes is an acceptable means of providing pragmatic validity (van Aken et al. 2016).

Future research should examine the other CLBMs identified in the content analysis as well as the three other crowdbased strategies identified in the Delphi process for sharing office space, procuring office staffing, and procuring knowledge-based services. Future research should also expand on the idea of B2Crowd relationships by examining governance issues, competitive collaboration, and how the role of the firm changes in such a relationship. Additionally, because empirical performance data may not be easily obtainable by researchers, simulation may provide a means for further testing the generic design in the contexts found during the current study.

Conclusion

This design science research effort yielded two outcomes. First, an explanation was provided regarding how the integration of CLBMs into omnichannel supply chains would impact the value cocreation process. The idea of “competitive collaboration” synthesized from previous literature, where firms have to compete with the crowd members’ alternative interests, is identified as the specific mechanism altering the value cocreation process. Second, a generic design for the integration of CLBMs into an omnichannel logistics strategy in terms of contexts and design considerations was provided. Consensus of expert opinion was provided to demonstrate the pragmatic validity of the generic design as well. CLBMs provide an enticing but challenging means of improving OSCM performance in omnichannel logistics but require further study to continue elucidating their roles.

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Appendix A – Tables

Table 6 - Content Sources

Source	Description	Website
Acquity Group	E-commerce and digital marketing company	AcquityGroup.com
Commercial Carrier Journal	Online publication for fleet management	CCJDigital.com
Eye for Transport	Supply chain and logistics news publication	EFT.com
Fortune	Online business news	Fortune.com
GeekWire	Online publication for new technology and startups	GeekWire.com
Global E-Commerce Facts	Online business news	E-commerceFacts.com
Inc.	Magazine about small business and startups	Inc.com
Logistics Management	Online publication	LogisticsMgmt.com
Modern Materials Handling	Online publication	MMH.com
New York Times	Business and news publication	NYT.com
SCM World	Trade Publication for Supply Chain Management professionals	SCMWorld.com
Supply Chain 24/7	Trade Publication for Transportation, Distribution, Logistics, and Supply Chain Management	SupplyChain247.com
Supply Chain Management Review	Online publication	SCMR.com
Techcrunch	Online publication for new technology and startups	Techcrunch.com
TechTimes	Online publication for new technology and startups	TechTimes.com
The Economist	Business and news publication	Economist.com
The Metropolitan Corporate Counsel	Online publication	MetroCorpCounsel.com
Wall Street Journal	Business and news publication	WSJ.com

Table 7 - Description of Content Categories and Coding Rules

Category	Description	Coding Rule	Example Recording Units
CLBM	A Crowdbased Logistics Business Model (CLBM) refers to any innovative adaptation of the sharing economy or gig economy business model for use in logistics or supply chain strategy.	Assign to this content category if the recording unit describes any logistics or supply chain business model that can be considered an adaptation of the sharing or gig economy business model.	"The platform is a peer-to-peer app on your smartphone. This idea of a sharing economy offers even new possibilities. Same day delivery is now within reach. Parcels which normally would be picked up to be transferred to a distribution center have the ability to reach the customer instantly and for a competitive price."
Strategy Integration	Refers to how CLBMs are integrated into logistics, operations, or supply chain strategy.	Assign to this content category if the recording unit addresses how the CLBM can be integrated into logistics, operations, or supply chain strategy. It may include a description of how a particular CLBM is being used in practice, where in the supply chain the CLBM can be used, what industries it is used in, or the geographical region in which it is used.	"Companies may use employees or independent contractors to deliver each order, although there exists debate as to the best classification for such delivery people" "It is possible that in North America there could be an evolution in that the pace of omnichannel adoption is growing, with shippers looking to potentially bypass standard existing providers in exchange for better flexibility and timeliness"

Table 7 Continued

Category	Description	Coding Rule	Example Recording Units
Performance Dimensions	Refers to an outcome of integrating a CLBM either in terms of logistics performance (effectiveness and efficiency), operational performance (cost, quality, delivery, flexibility, and innovation), or economic/financial performance.	Assign to this content category if the recording unit refers to how a particular CLBM may gain a competitive advantage or impact a particular performance outcome, such as increasing logistics effectiveness or efficiency (Konrad and Mentzer 1991; Fugate et al. 2010), increasing agility (Gligor et al. 2015), or improving operational performance in terms of Cost, Quality, Flexibility, Innovation, and/or Delivery (Krause et al. 2001; Kroes and Ghosh 2011; Spring et al. 2017).	"By partnering with a crowdshipper, they can turn their vast networks of physical stores into distribution hubs for online purchases, giving them a competitive advantage in the race for same-day delivery" "Capacity isn't capped as it might be at a 3PL facility" "With its technology and low overhead, Keychain is able to keep its margin between 6 and 12 percent of the shipment, which Kulp said is lower than other brokers."
Concerns	Refers to any issues or obstacles to implementing a CLBM such as regulatory concerns or contractor screening & onboarding.	Assign to this content category if the recording unit describes obstacles to implementation of the CLBM, general concerns that a company should have regarding the CLBM, or how information about how to overcome the obstacle.	"There are a lot of potential issues, including legal questions, liability concerns, and reputational risks." "But for all the speed and mobility an evolving new model like this brings, there are tried-and-true, ironclad laws of physics, geography and time that need to be respected by newcomers to the industry."

Table 8 - Content Analysis Results

CLBM	Description	Example Companies	Relevant Supply Chain Tier	Value Cocreation Relationship Type	Last Mile Fulfillment Category
Crowdsourced Logistics (CSL)	A shipper crowdsources private individuals who share use of their privately owned vehicles to deliver goods to online customers	Amazon Flex, ReturnRunners, GrubHub	Last Mile, Upstream	B2Crowd	P2C
Über for Trucking	Shippers and carriers are connected through an electronic exchange in a way that increases speed and transparency	Transfix, Cargomatic	Upstream	B2B or B2Crowd	N/A
Logistics Asset Sharing	Sharing logistics assets such as warehousing or delivery fleets between firms through an electronic exchange	Flexe, FLOOW2	Upstream	B2B	N/A
Click and Collect (aka Buy Online, Pickup in Store or BOPIS)	Customers buy products online, then pickup the products in store, effectively sharing their personally owned vehicle assets to transport goods over the final mile	Walmart, The Home Deport	Last Mile	B2C	C2P
Pickup Point Networks (PPN)	Customers buy products online, then pickup the products from a node in a network of pickup points, effectively sharing their personally owned vehicle assets to transport goods over the final mile	Amazon Locker, UPS	Last Mile	B2C	C2P
Crowdshipping	In-store shoppers or employees finishing a shift are recruited and compensated to make deliveries to online shoppers in nearby areas	Walmart	Last Mile	B2Crowd	P2C
Bicycle Couriers	A shipper crowdsources bicycle messengers and couriers to deliver small packages and parcels in urban areas	UberRUSH	Last Mile	B2Crowd	P2C

Table 9 - Expert Panel Demographics

Round 1 (N = 35)									
Position Title	**#**	**Company Type**	**#**	**Experience**	**#**	**Firm Size (Annual Revenue)**	**#**	**Region**	**#**
C-Suite Executive (CEO, COO, etc)	8	Retailer	7	< 5 years	3	< $1M	5	USA - West Coast	8
Vice President	5	3PL	15	5-10 years	1	$1M - $100M	6	USA - Midwest	7
Director	11	Distributor	1	10-20 years	8	$100M - $1B	3	USA - Southeast	9
Manager	8	Manufacturer	5	> 20 years	23	> $1B	21	USA - Northeast	5
Other	3	Consultant	5					Canada	3
		IT	2					UK	2
								Australia	1

Round 2 (N = 15)									
Position Title	**#**	**Company Type**	**#**	**Experience**	**#**	**Firm Size (Annual Revenue)**	**#**	**Region**	**#**
C-Suite Executive (CEO, COO, etc)	4	Retailer	2	10-20 years	6	< $1M	3	USA - West Coast	1
Vice President	1	3PL	8	> 20 years	9	$1M - $100M	2	USA - Midwest	1
Director	2	Manufacturer	2			$100M - $1B	1	USA - Southeast	7
Manager	6	Consultant	3			> $1B	9	USA - Northeast	3
Other	2							UK	1
								Australia	1
								China	1

Table 10 - Round #1 Results

CLBM	Count
Crowdsourced Logistics (CSL)	22
Buy Online, Pickup in Store (BOPIS)	8
Pickup Point Networks (PPN)	8
Über for Trucking	7
Logistics Asset Sharing	3
Crowdshipping	3
Bicycle Couriers	1
Warehouse Staffing Procurement	1
Other Crowdbased Strategies	
Office Staffing Procurement	1
Office Space Sharing	1
Knowledge-based Service Procurement	1
Design Considerations	
Contextual Variables Likely to Enable Success	
Population Density	
Urban Areas	16
Rural Areas	5
Urgency of Delivery	
Same-day Delivery	6
Time-insensitive Delivery	2
Product Characteristics	
High-value Goods	
Pharmaceuticals Home Delivery	5
White Glove Service	5
Low-value Goods	
Small Parcel Delivery	14
Grocery Home Delivery	7
On-demand Meal Delivery	5
Concerns & Risks of Implementation	
Liability & Insurance	22
Customer Experience	10
Operational Issues	16
Regulatory Issues	13
Employee/Contractor Reliability & Performance	14
Economic Sustainability of the CLBM	6
IT Integration	5
Governance and Agency Issues	4

Table 11 - Round #2 Results: Descriptive Statistics

	Expected Impact on Traditional OSCM Performance Measures																			
	Cost		**Logistics Service Quality**		**Innovation**		**Flexibility**		**Delivery in Urban Areas**		**Delivery in Rural Areas**		**Same-Day Delivery**		**Non-Time Sensitive Delivery**		**Delivery of Low Value Products**		**Delivery of High Value Products**	
	M	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
CSL	3.27	1.71	3.80	1.57	4.93	1.53	5.33	1.45	4.73	1.87	4.00	1.41	5.53	1.55	5.07	1.67	4.87	1.19	4.00	1.77
Über for Trucking	3.85	1.07	4.08	1.32	5.08	1.19	5.31	1.03	4.85	1.21	4.46	1.39	4.31	1.44	4.77	1.01	4.54	0.88	4.08	1.12
Logistics Asset Sharing	3.62	1.33	4.23	1.09	5.31	1.18	5.54	0.78	4.85	0.99	4.54	1.13	5.15	0.80	5.00	0.82	4.92	0.76	4.38	1.04
BOPIS	2.54	1.66	5.31	0.95	5.08	1.19	4.85	1.52	5.54	1.20	4.38	2.02	5.69	1.25	5.46	1.51	5.08	1.44	6.00	0.74
PPN	3.31	2.06	4.69	1.44	5.38	0.87	5.38	1.04	5.77	0.60	4.46	1.85	4.69	1.32	5.69	1.03	4.69	1.38	4.46	1.05

Table 12 - Round #2 Results: Measure of Consensus of Expected Impact on OSCM Performance Factors and Contextual Variables

	Critical SM @ α = 0.05	Observed SM	p-val	Weighted Sums of Centered Ranks: Cost	Logistics Service Quality	Innovation	Flexibility	Delivery in Urban Areas	Delivery in Rural Areas	Same-Day Delivery	Non-Time Sensitive Delivery	Delivery of Low Value Products	Delivery of High Value Products
CSL	22.85	29.93	0.00	-29.77	-24.02	7.83	22.98	8.36	-24.02	32.90	15.67	9.40	-19.32
Über for Trucking	20.43	20.60	0.02	-21.93	-16.19	17.23	31.86	13.06	-2.09	-8.36	7.31	-3.13	-17.76
Logistics Asset Sharing	20.57	28.13	0.00	-32.38	-26.11	22.46	27.68	2.61	-5.74	16.19	7.31	4.70	-16.71
BOPIS	20.30	25.65	0.00	-41.96	6.19	-4.62	-12.46	11.04	-11.67	21.62	9.32	0.60	21.93
PPN	20.41	23.07	0.01	-31.86	-5.22	11.49	10.44	27.16	-8.88	-5.22	24.02	-5.74	-16.19

Table 13 - Round #2 Results: Measure of Consensus on Importance of Design Considerations

	Critical SM @ α = 0.05	Observed SM	p-val	Weighted Sums of Centered Ranks								
				Liability & Insurance	Customer Experience	Operational Issues	Regulations	Contractor or Employee Screening	Revenue Model	IT Integration	Governance and Agency Issues	Brand Reputation
CSL	14.37	17.48	0.03	-6.57	-24.10	-30.67	17.53	8.76	8.76	7.67	16.43	2.19
Über for Trucking Logistics	13.05	18.45	0.01	8.66	-28.29	-15.01	24.83	4.62	5.20	-1.73	n/a	1.73
Asset Sharing	12.01	22.25	0.00	-2.45	-3.67	-34.29	20.82	14.70	0.00	4.90	n/a	n/a
BOPIS	10.16	41.75	0.00	25.72	-26.94	-26.94	29.39	18.37	n/a	-9.80	n/a	-9.80
PPN	8.90	22.47	0.00	-1.41	-4.24	-16.97	31.11	n/a	-8.49	n/a	n/a	n/a

Appendix B – Delphi Questionnaires

	Round 1
1	What Crowdbased Logistics Business Models are you aware of that are being developed in your industry? If you're not aware of any specific Crowdbased Logistics Model currently being experimented with, of the examples given in the footnote above, which ones could in your opinion work in your industry? Please list no more than five.
2	Who do you think are the relevant actors in a Crowdbased Logistics Business Model? That is, who are the key players that will make a difference in whether such a model is successful or not? Why? Please list no more than seven organizations, entities, individuals, or categories of individuals.
3	In which industries, product segments within an industry, or geographical regions would you expect Crowdbased Logistics Business Models to most likely succeed? Why? Please list no more than seven items.
4	What general concerns or questions about the use of Crowdbased Logistics Business Models would have to be addressed before you would consider employing them?

Round 2

#	CLBM	Question
1	CSL	What would you expect the impact to be on each of the following performance outcomes when using Crowdsourced Logistics (that is, making deliveries with sharing economy workers using their personally owned vehicles) for last mile delivery, transshipments, or reverse logistics (that is, returns for online customers)? Please move the slider to reflect, in your professional opinion, whether you expect each outcome to be "Increased" or "Reduced" based on the use of this CBLM. As a reminder, Crowdsourced Logistics (CSL) can be used for last mile delivery, transshipments between stores or DCs, and reverse logistics. Examples include AmazonFlex, LaLaMove, GoGoVan, Return Runners, and HappyReturns.

#	Performance Outcome	Reduced	No Impact	Increased
1	Ability to deliver throughout densely populated urban areas	1	4	7
2	Ability to perform same-day deliveries	1	4	7
3	Cost in the last mile of the supply chain	1	4	7
4	Ability to deliver in less populated suburban or rural areas	1	4	7
5	Ability to deliver low cost items such as consumer packaged goods, groceries, or apparel	1	4	7
6	Customer service levels in last mile delivery	1	4	7
7	Innovation in the last mile of the supply chain	1	4	7
8	Ability to perform deliveries without hard time windows (2 or 5 day deliveries for example)	1	4	7
9	Flexibility in the last mile of the supply chain	1	4	7

	10	Ability to deliver high-value items like computers, TVs, or other electronics	1	4	7
2	CSL	Listed below are some of the concerns identified in the first survey phase as being important issues to resolve before using Crowdbased Logistics Business Models in general. When wanting to use Crowdsourced Logistics (CSL) specifically (that is, making deliveries with sharing economy workers using their personally owned vehicles) for last mile delivery, transshipments, or reverse logistics, which of these concerns are most important? From this list, please choose 4 items from the list on the left that in your opinion are most important and move them to the group on the right. Then place them in order of importance (that is, #1 should be the most pressing issue, #2 the second-most, etc.) to reflect what would have to be resolved first before you were to employ CSL in your supply chain.			
	#	**Concerns or Risks**			
	1	Liability and Insurance			
	2	Poor customer experience or customer service quality			
	3	Operational issues including driver performance, dealing with delivery site characteristics like gate codes or hours of operation; employee training; ensuring adequate staffing; driver delivery vehicle capacity			
	4	Regulatory concerns (how does the government view CSL?)			
	5	Contractor/Driver Screening			
	6	Revenue model - unsustainable economics (does CSL pay for itself or does it need to be subsidized from other sources?)			
	7	How well can the provider integrate with existing IT infrastructure?			
	8	Governance and agency issues (e.g., who is ultimately responsible for the last mile experience?)			
	9	Protecting the shipper's brand			
3	Über for Trucking	What would you expect the impact to be on each of the following performance outcomes when using Electronic Marketplaces such as Transfix, Cargomatic, or UberFreight to procure transportation services (that is, procuring TL/LTL freight hauling directly from the provider through the platform)? Please move the slider to reflect, in your professional opinion, whether you expect each outcome to be "Increased" or "Reduced" based on the use of this CBLM As a reminder, companies today are beginning to coordinate TL/LTL freight brokering & forwarding through electronic marketplaces such as UberFreight, Transfix, or Cargomatic.			
	#	**Performance Outcome**	**Reduced**	**No Impact**	**Increased**
	1	Ability to deliver to densely populated urban areas	1	4	7

	2	Ability to perform time-sensitive deliveries	1	4	7
	3	Transportation costs in the supply chain	1	4	7
	4	Ability to deliver to less populated suburban or rural areas	1	4	7
	5	Ability to deliver low cost items such as consumer packaged goods, groceries, or apparel	1	4	7
	6	Customer service levels in the supply chain	1	4	7
	7	Innovation in the the supply chain	1	4	7
	8	Ability to perform deliveries without hard time windows	1	4	7
	9	Flexibility in the supply chain	1	4	7
	10	Ability to deliver high-value items like computers, TVs, or other electronics	1	4	7
4	Über for Trucking	Listed below are some of the concerns identified in the first survey phase as being important issues to resolve before using Crowdbased Logistics Business Models in general. When wanting to use Electronic Marketplaces to procure transportation services, which of these concerns are most important? From this list, please choose 4 items from the list on the left that in your opinion are most important and move them to the group on the right. Then place them in order of importance (that is, #1 should be the most pressing issue, #2 the second-most, etc.) to reflect what would have to be resolved first before you were to use these services in your supply chain.			
	#	**Concerns or Risks**			
	1	Liability and Insurance			
	2	Poor customer experience or customer service quality			
	3	Operational issues			
	4	Regulatory concerns			
	5	Contractor Screening			
	6	Revenue model			
	7	How well can the provider integrate with existing IT infrastructure?			
	8	Protecting the shipper's brand			
5	Logistics Asset Sharing	What would you expect the impact to be on each of the following performance outcomes when using Electronic Marketplaces such as Flexe or FLOOW2 to share logistics assets between companies (for example, sharing warehouse capacity or owned transportation assets)? Please move the slider to reflect, in your professional opinion, whether you expect each outcome to be "Increased" or "Reduced" based on the use of this CBLM As a reminder, some companies are sharing logistics assets with other businesses through electronic marketplaces. For example, companies can share storage space and warehousing capabilities through marketplaces such as Flexe, which provides a service akin to Airbnb, or share vehicles between companies through platforms such as FLOOW2.			

#	Performance Outcome	Reduced	No Impact	Increased
1	Ability to reach or operate in densely populated urban areas	1	4	7
2	Ability to perform faster deliveries to customers	1	4	7
3	Transportation costs in the supply chain	1	4	7
4	Ability to reach less populated suburban or rural areas	1	4	7
5	Ability to deliver low cost items such as consumer packaged goods, groceries, or apparel	1	4	7
6	Customer service levels in the supply chain	1	4	7
7	Innovation in the the supply chain	1	4	7
8	Ability to perform deliveries without hard time windows	1	4	7
9	Flexibility in the supply chain	1	4	7
10	Ability to deliver high-value items like computers, TVs, or other electronics	1	4	7

6	Logistics Asset Sharing	Listed below are some of the concerns identified in the first survey phase as being important issues to resolve before using Crowdbased Logistics Business Models in general. When wanting to use Electronic Marketplaces to share logistics assets between companies, which of these concerns are most important? From this list, please choose 4 items from the list on the left that in your opinion are most important and move them to the group on the right. Then place them in order of importance (that is, #1 should be the most pressing issue, #2 the second-most, etc.) to reflect what would have to be resolved first before you were to use these services in your supply chain.

#	Concerns or Risks
1	Liability and Insurance
2	Poor customer experience or customer service quality
3	Operational issues such as coordinating shipments between contracted warehouse operators or availability of other logistics assets
4	Regulatory concerns (how does the government view these services?)
5	Contractor Screening
6	Revenue model
7	How well can the provider integrate with existing IT infrastructure?

7	BOPIS	What would you expect the impact to be on each of the following performance outcomes when using BOPIS (that is, customers purchasing goods online and picking them up in store)? Please move the slider to reflect, in your professional opinion, whether you expect each outcome to be "Increased" or "Reduced" based on the use of this CBLM Many retailers are using Buy Online, Pickup In Store (BOPIS), also known as "Click and Collect" or "In-Store Pickups", where shoppers make purchases via website/mobile platform and employees at a nearby storefront pick the order and have it waiting for the consumer within a certain timeframe.

#	Performance Outcome	Reduced	No Impact	Increased
1	Ability to provide access to goods in densely populated urban areas	1	4	7
2	Ability to allow customers to access orders on the same day	1	4	7
3	Transportation cost in the last mile of the supply chain	1	4	7
4	Ability to serve customers in less populated suburban or rural areas	1	4	7
5	Ability to provide low cost items such as consumer packaged goods, groceries, or apparel	1	4	7
6	Customer service levels	1	4	7
7	Innovation in the last mile of the supply chain	1	4	7
8	Ability to broaden time windows in which to serve customers	1	4	7
9	Flexibility in the last mile of the supply chain	1	4	7
10	Ability to provide access to high-value items like computers, TVs, or other electronics	1	4	7

8	BOPIS	Listed below are some of the concerns identified in the first survey phase as being important issues to resolve before using Crowdbased Logistics Business Models in general. When wanting to use BOPUS, which of these concerns are most important? From this list, please choose 4 items from the list on the left that in your opinion are most important and move them to the group on the right. Then place them in order of importance (that is, #1 should be the most pressing issue, #2 the second-most, etc.) to reflect what would have to be resolved first before you were to use these services in your supply chain.

#	Concerns or Risks
1	Liability and Insurance
2	Poor customer experience or customer service quality
3	Operational issues, employee reliability, and employee performance (e.g., employee training; ensuring adequate staffing; capacity for added services)
4	Regulatory concerns

	5	Employee Screening			
	6	How well can the provider integrate with existing IT infrastructure?			
	7	Protecting the shipper's brand			

9	PPN	What would you expect the impact to be on each of the following performance outcomes when using Pickup Point Networks (PPN) (that is, customers purchasing goods online and picking them up from a secure location within a geographical region)? Please move the slider to reflect, in your professional opinion, whether you expect each outcome to be "Increased" or "Reduced" based on the use of this CBLM. As a reminder, Pickup Point Networks (PPN) are similar to BOPUS in that customers shop online and pickup their own packages from a secure location but the pickup points are a network of secure lockboxes or locations. Amazon Locker is an example of a PPN.			
	#	**Performance Outcome**	**Reduced**	**No Impact**	**Increased**
	1	Ability to provide access to goods in densely populated urban areas	1	4	7
	2	Ability to allow customers to access orders on the same day	1	4	7
	3	Transportation costs in the last mile of the supply chain	1	4	7
	4	Ability to serve customers in less populated suburban or rural areas	1	4	7
	5	Ability to provide low cost items such as consumer packaged goods, groceries, or apparel	1	4	7
	6	Customer service levels	1	4	7
	7	Innovation in the last mile of the supply chain	1	4	7
	8	Ability to broaden time windows in which to serve customers	1	4	7
	9	Flexibility in the last mile of the supply chain	1	4	7
	10	Ability to provide access to high-value items like computers, TVs, or other electronics	1	4	7

10	PPN	Listed below are some of the concerns identified in the first survey phase as being important issues to resolve before using Crowdbased Logistics Business Models in general. When wanting to use a PPN, which of these concerns are most important? From this list, please choose 4 items from the list on the left that in your opinion are most important and move them to the group on the right. Then place them in order of importance (that is, #1 should be the most pressing issue, #2 the second-most, etc.) to reflect what would have to be resolved first before you were to use these services in your supply chain.
	#	**Concerns or Risks**
	1	Liability and Insurance
	2	Poor customer experience or customer service quality

3	Operational issues such as integrating pickups or deliveries routes at each PPN location
4	Regulatory concerns
5	Revenue model (does a PPN pay for itself or does it need to be subsidized from other sources?)

IV. THE LOGISTICS COST-SERVICE TRADEOFF WITH CROWDSOURCED AND HYBRID LAST MILE DELIVERY FLEETS

Abstract

Retail logistics and supply chain managers face increasing pressure to develop cost efficient and responsive delivery operations for e-commerce channels. Some companies have begun testing new business models inspired by the sharing economy, where independent contractors are crowdsourced on a per-task basis to provide last mile delivery using personal vehicles. While managerial interest in this phenomenon continues to rise, the role of crowdsourcing last mile delivery in logistics strategy and the impact on retailers' competitive advantage remains under-examined in academia. This research develops and applies an empirically grounded simulation optimization model to create insight into how crowdsourced delivery impacts financial and operational performance in the last mile. Using one-years' worth of home delivery data from a nationally prominent retail pharmacy from 2016-2017, the research shows how crowdsourced delivery's impact on performance varies depending on logistics strategy (in terms of Minimize Cost or Maximize Responsiveness), fulfillment policy (in terms of Ship from Store or Ship from DC), product type (in terms of Functional or Innovative), and fleet costs. Implications for how crowdsourcing can be integrated into last mile logistics strategy are discussed.

Introduction

E-commerce continues to grow at increasingly faster rates. In 2017, online sales in the United States grew by 16.9% from 2016, which was a 15.9% increase from 2015, which had grown by 14.0% from year 2014 (U.S. Census Bureau 2018). Comparatively, total retail sales only grew by 4.8% in 2017, 2.6% in 2016, and 1.93% in 2015 from the preceding year. Coupled with increasingly stringent online customer demands for speedy delivery, the year-over-year sales growth of e-commerce highlights the importance of ensuring cost efficient and responsive last mile logistics operations are in place for the online channel. Finding the right balance between cost efficiency and responsiveness in the last mile of the supply chain can be a source of competitive advantage for retailers (Esper et al. 2003; Qi et al. 2017; Steinker, Hoberg, and Thonemann 2017).

To improve cost efficiency and responsiveness in last mile delivery strategies, many retailers are experimenting with new technologies and novel business models inspired by crowdsourcing and the sharing economy (Howe 2006; Bayus 2013; Ba and Nault 2017). The “Uber-for-logistics” business model is one where crowd members make deliveries on behalf of a shipper by sharing access to personally owned vehicle assets. Many terms have emerged to describe this novel business model, including “crowdsourced logistics” (Castillo et al. 2017), “crowd delivery” (Carbone, Rouquet, and Roussat 2017), “crowdsourcing shared mobility” (Qi et al. 2017), and “crowdshipping” (Dayarian and Savelsbergh 2017). Scholarly interest in these business models along with other crowdbased logistics strategies such as shared warehousing, B2B asset sharing, and crowd freight transportation is beginning to grow. One set of pressing questions about crowdbased logistics phenomena relates to how this class of business models impacts competitive advantage generated through logistics operations.

One approach for understanding crowdsourced delivery's impact on competitive advantage derived from last mile logistics operations is to study the financial and operational performance of a delivery fleet comprised of crowdsourced drivers under various contextual conditions. Understanding how crowdsourced delivery performs financially and operationally in different scenarios can provide insight to how to infuse the new business model into existing logistics and operations strategies. Specifically, how does performance of a crowdsourced fleet of delivery drivers differ between logistics strategies that attempt to either minimize cost or maximize responsiveness (Christopher and Towill 2001; Shen and Daskin 2005; Goldsby, Griffis, and Roath 2006)? Additionally, how does crowdsourced delivery's performance change when the types of products being delivered change from innovative to functional types with different demand characteristics (Fisher 1997; Lee 2002)? Furthermore, can crowdsourced delivery be combined with traditional, dedicated delivery modes to create hybrid delivery fleets; and if so, how should such a fleet be designed? The implications proposed by questions such as these can shed light into how crowdsourced delivery impacts retailer competitive advantage through logistics operations.

The current research effort asks three guiding research questions to provide initial insight into the logistics strategy implications of crowdsourced delivery: *1) How do dedicated and crowdsourced fleets compare in terms of profitability when providing* *home delivery services? 2) What is the optimal size and mix of a hybrid dedicated-crowdsourced fleet when providing same day delivery of various product types in an omnichannel network? 3) What is the nature of the cost-service tradeoff when using a hybrid fleet comprised of both dedicated and crowdsourced drivers?* To explore these research questions, an empirically grounded simulation optimization is developed that 1) compares crowdsourced with dedicated delivery in terms of financial performance, and 2) examines the cost-service tradeoff when conducting same day deliveries with a hybrid fleet of delivery drivers.

In exploring these guiding research questions, three contributions are made. First, the results indicate that crowdsourcing home delivery may be a source of more profitable and more responsive capacity relative to a dedicated fleet of delivery drivers. However, the lower costs associated with crowdsourcing come with additional risks since crowdsourced drivers are essentially amateurs with greater autonomy over their own work schedules. Second, when using hybrid fleets comprised of crowdsourced and dedicated delivery drivers, the requisite size and fleet mix changes depending on the types of products being delivered, whether deliveries are being made from nearby retail stores or a central distribution center (DC), and whether a cost minimization or responsiveness maximization logistics strategy is being pursued. Finally, this research shows that the tradeoff between cost effectiveness and responsiveness is highly dependent on fleet costs, where the cost for dedicated delivery is determined on a per-mile basis whereas cost for crowdsourced delivery is determined on a per-task basis.

The remainder of the paper is organized as follows. First, a brief review of relevant literature on crowdsourcing and logistics topics is presented. This is followed by an overview of the simulation optimization methodology used to explore the research questions. The two studies are then presented along with discussion of their results. Finally, a summary discussion of the major conclusions from this research effort is provided.

Literature Review

While the body of literature on crowdbased logistics phenomena remains nascent, academic interest in this domain has begun to blossom. Most research has been exploratory in nature, seeking to elucidate how business strategies inspired by the recent emergence of the sharing (or “gig”) economy can be applied to logistics operations. For example, Carbone et al. (2017) content analyze websites of 57 startups to identify categories of logistics strategies that either utilize crowdsourcing or asset sharing between firms. The authors find that most of the new business models fall into four areas: warehousing and storage, delivery, freight shipping, and freight forwarding.

Other exploratory research examines the inner workings of crowdbased strategies to assess their feasibility in certain contexts. For instance, Wang et al. (2016) develop an analytical model to assign deliveries to crowd members from parcel stations in a pickup point network to customer locations. Using empirical data from southeast Asia, the authors show how delivery tasks can be assigned to crowd members to minimize logistics costs. Archetti, Savelsbergh, and Speranza (2016) and Arslan et al. (2016)

develop variations of the classic vehicle routing problem (VRP) to study how delivery operations with crowdsourced drivers can also be analyzed analytically. Qi et al. (2017) find that scalability of crowdsourced delivery is dependent upon the ability to maintain a sufficient pool of potential drivers (i.e. a large enough crowd). Ultimately though, the feasibility of any crowdbased logistics strategies depends on customers' perceptions of the service quality from crowd members (Punel and Stathopoulos 2017).

Some scholars have also considered the role of crowdbased logistics strategies in urban logistics design (Kunze 2016; Savelsbergh and Van Woensel 2016). For instance, by 2030, some European cities may begin to develop networks of electronic drop boxes to facilitate last mile transport (Kunze 2016; Wang et al. 2016). There is also a need for collaborative business models where companies share large capital-intensive assets (Matzler, Veider, and Kathan 2015), especially in urban areas where logistics infrastructure capacity is limited (Savelsbergh and Van Woensel 2016).

The application of crowdbased business models to reverse logistics has also been proposed (Chen et al. 2016; Castillo et al. 2017) as have calls for studying their impact on environmental sustainability (Paloheimo, Lettenmeier, and Waris 2016; Buldeo Rai et al. 2017; Kafle, Zou, and Lin 2017). Paloheimo et al. (2016) show how crowdsourcing on-demand book delivery from local libraries in Finland reduces carbon footprints of the standard delivery operations. Kafle et al. (2017) find that crowdsourcing delivery reduces vehicle-miles traveled and consequently, emissions, thus contributing to environmental sustainability.

Castillo et al. (2017) simulated using crowdsourced drivers in New York City to make on-demand deliveries. The authors found that even though crowdsourced logistics appears to be relatively cheap and a source of increased responsiveness in the last mile of the supply chain, a finding supported by Qi et al. (2017), it adds additional risk in terms of logistics service quality and reliability. One method for reducing the added risk is to assign crowdsourced drivers to deliver within their own social networks, although the technology for facilitating this continues to evolve (Suh, Smith, and Linhoff 2012; Devari, Nikolaev, and He 2017). Thus, crowdsourcing is likely best used as excess delivery capacity for a baseline fleet of dedicated delivery vehicles, rather than as a primary delivery strategy. In such a scenario, using a hybrid delivery fleet of dedicated and crowdsourced drivers may be a means of providing retailers with agile, flexible, and cost effective last mile delivery service. This finding implies a novel problem however: optimizing the size and ratio of dedicated-to-crowdsourced drivers that either minimizes cost or maximizes responsiveness. This problem has yet to be addressed in the literature and is the impetus for examining the financial and operational performance of a hybrid fleet of drivers for same day delivery.

Methodology

To explore this study's research questions, a multi-study approach is adopted to create insight into how crowdsourced delivery may impact last mile logistics strategy. The overarching methodological approach is to compare crowdsourced delivery with traditional last mile delivery in terms of expected financial and operational performance using an empirically grounded simulation optimization model. The first study develops a multimethod simulation that combines discrete event (Law 2015; Kelton 2016) and agent-based methodologies (Macal and North 2010; Kasaie and Kelton 2015) to examine the profitability of crowdsourced delivery. The financial performance (in terms of customer delivery fees and delivery costs) of a traditional dedicated last mile delivery fleet is compared with the performance of a delivery fleet that is entirely crowdsourced. Delivery data spanning a one-year period from July 2016 – July 2017 on Staten Island in New York City are used to simulate the last mile environment in which this study takes place. The data were provided by a nationally prominent retail pharmacy and its 3PL provider contracted to manage prescription home delivery operations across the United States. The objective of Study 1 is to compare the profitability of each fleet type for scheduled deliveries under different last mile logistics strategies by simulating home delivery with both dedicated and crowdsourced fleets using the empirical data. This comparison provides initial insight into the financial performance of crowdsourcing last mile delivery.

To explore the second and third research questions, Study 2 introduces same day delivery to the standard scheduled delivery operations provided by the retail pharmacy company. Study 2 is an explorative effort that examines same day delivery services with a hybrid fleet comprised of both dedicated and crowdsourced drivers. The goal in Study 2 is to gain insight into the operational performance of a hybrid fleet of delivery drivers in terms of the delivery cost-responsiveness tradeoff. A simulation optimization (April et al. 2003; Fu, Glover, and April 2005; Amaran et al. 2015) using a scatter search metaheuristic (Glover, Laguna, and Martí 2000; Martí, Laguna, and Glover 2006) is employed to find near-optimal hybrid fleet mixes that either minimize cost or maximize responsiveness. Expected system-level delivery costs and average order fulfillment times are generated for varying fleet sizes and mixes, where both outcomes are also dependent upon the specific costs of each fleet type. The objective of Study 2 is to create system-level understanding of how fulfillment policy, product characteristics, and delivery cost impact the hybrid fleet mix and the subsequent last mile cost-customer service tradeoff.

Study 1 – Profitability of Dedicated and Crowdsourced Delivery

The first study builds upon previous research suggesting that crowdsourced logistics may be a means of increasing flexibility and responsiveness in the last mile (Castillo et al. 2017). The current study provides initial insight to the comparative delivery cost between a crowdsourced and dedicated fleet of delivery drivers. Because crowdsourcing delivery is a nascent phenomenon not yet widely adopted in practice and thus real-world companies are difficult to come by, an empirically grounded simulation model is used (Evers and Wan 2012). Specifically, discrete event and agent-based methods are combined into a single simulation that provides nascent insight into how financial performance of home delivery services changes when switching from a dedicated to a crowdsourced fleet.

The purpose of combining discrete event and agent-based techniques is to create a holistic understanding of the omnichannel fulfillment system being modeled. Discrete event techniques typically follow a “top-down” approach where systems are modeled as a network of processes, and the changes affecting outputs occur at discrete times (Law 2015; Kelton 2016). Conversely, agent-based modeling adopts a “bottom-up” approach where a system can be analyzed from the perspective of its essential agents (Kasaie and Kelton 2015). Because crowdsourcing delivery introduces a new social dimension emanating from the autonomy of sharing economy workers (Castillo et al. 2017), studying microlevel behaviors of individual drivers is critical to understanding system-level responses. Therefore, agent-based techniques where entities are modeled as agents with their own behavior patterns were added to the discrete events in this study, so insight could be gained about drivers’ interactions with the omnichannel fulfillment system.

Previously established procedures for developing rigorous simulation models were used (Law and Kelton 1982; Sargent 2005; Kasaie and Kelton 2015; Law 2015; Kelton 2016). In the ensuing sections, the problem at hand is described along with the assumptions made in the simulation. This is followed by description of the data collection process and the input and outcome variables. Next, details are provided about the verification and validation process of the simulation model. Finally, information about the simulation and analysis technique is presented as well as a brief discussion of the Study 1 results.

Problem Description.

The simulation is set on Staten Island, NY, which has natural geographical boundaries that create a suitable environment in which to study intracity delivery. Customers call in or place orders online to schedule prescription home delivery. Orders are then processed at the nearest fulfillment point (retail store or a distribution center) and batched into a service route for pickup and home delivery by a delivery agent the next day. Service routes consist of a certain number of customers, governed by an empirically-derived probability distribution. Each day, a driver picks up the prescriptions, makes all deliveries along the route, then returns to the fulfillment point to return prescription signature receipts.

The following assumptions are made to ensure tractability while maintaining validity and realism of the simulation model. First, because the focus of this study is on the delivery aspect of omnichannel strategy, rather than inventory quantities or inventory positioning within the network, inventory is assumed to always be available at the fulfillment point when it is needed. This aligns with the concerns of the retail pharmacy's 3PL since it is responsible for managing the home delivery operation and not inventory management. Next, since prescriptions are small parcels being delivered in relatively small quantities, the vehicles in the model are considered uncapacitated. All orders in a batch are delivered and once a driver picks up the batch of prescriptions, no enroute diversions are allowed. Finally, all orders received are delivered the next day, which means that time windows are not included (although order fulfillment times are considered in Study 2).

Data Collection.

The empirical data used in this study were provided by a nationally prominent retail pharmacy and the 3PL company that manages its prescription home delivery services throughout the United States. Covering a one-year period, the dataset consists of daily home deliveries (i.e. number of stops on a route) made from each storefront along with the destinations on Staten Island, NY from July 2016 – July 2017. The customer network from that year consists of 3,061 deliveries made to 445 unique customers from three retail storefronts on Staten Island, where each origin and destination was identified by its latitude and longitude coordinates (see Figure 7[c] for the simulated distribution and customer network).

The empirical delivery data was input into Stat::Fit in order to find the best fitting probability distribution that could be used to govern customer order generation in the simulation. The software package returned a Poisson distribution as being the best fit, which was also supported via visual inspection (see Figure 8). An intensity parameter of $\lambda = 3.0$ deliveries was returned from the Stat::Fit software to be used in the simulation package.

Other parameters used in the model were also obtained empirically. Customers are charged $5 for each home delivery, which is the standard price charged by the retail pharmacy. The cost per mile value for dedicated delivery comes from the DAT-Solutions database, which shows average last mile logistics cost per mile ranging from $2.40 in

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[c] All figures and tables are presented in the Appendix for this chapter.

Atlanta to $2.67 in Chicago (DAT 2018). Thus, using a dedicated delivery cost of $2.50 per mile for Staten Island, NY is comparable to these empirical costs. A cost of $3.00 per delivery is used for crowdsourced drivers, which was obtained via the driver training documentation a technology company that connects members of the crowd with shippers for same day delivery services.

Variables.

A 2x2x2 experimental design was used for Study 1. Omnichannel Fulfillment Policy refers to one of two policies that the company can choose for home delivery: Ship from Store (SFS) or Ship from DC (SFDC). These two variables are operationalized in the simulation by having deliveries made from all three retail stores (SFS) or only the lone store in the middle of Staten Island (SFDC). Product Type refers to delivering Innovative or Functional products (Fisher 1997; Lee 2002; Gligor, Esmark, and Holcomb 2015). Both levels of the Product Type variable are operationalized by demand volume, where Innovative products have low demand volume ($\lambda = 3$ stops per route) and Functional products have relatively higher demand volume ($\lambda = 6$ stops per route). Fleet Type refers to whether the deliveries are made by a driver from a Dedicated Fleet or a Crowdsourced Fleet. Because Study 1 is focused on a financial comparison of the fleet types, the main difference between them is how delivery costs are calculated. A dedicated driver's cost is based on the route length and per-mile cost whereas a crowdsourced driver’s is calculated on a per-delivery basis. Monthly Profitability was the single outcome variable used to compare the fleet types in the experimental design.

Revenue for the home delivery service is calculated on a per-order basis and the total cost for delivery is determined by the fleet type being used to perform the deliveries.

Conceptual Model Validity.

The conceptual model was developed through an ongoing dialogue with managers from the 3PL company, the retail pharmacy, and experienced academics not associated with the research project. This conceptualization of delivery operations eventually became the computer simulation model. The first step in the conceptual model is to determine where each customer requesting home delivery should be serviced from (as governed by the Omnichannel Fulfillment Policy being employed). In the simulation, the location of each customer and fulfillment point is plotted in GIS space. Then, each customer is assigned a parameter defining its nearest fulfillment point as calculated by route distance. Route lengths between fulfillment points and customer locations are obtained dynamically in the simulation via an application programming interface (API) with OpenStreetMaps.us servers.

The next step deals with order generation and processing and is modeled as a discrete event. In practice, the nearest fulfillment point receives customer orders and prepares them for next day delivery. To simulate this, each fulfillment point receives a quantity of orders within its area of responsibility each day. The quantity received for processing is set by one of the two Poisson probability distributions, depending on the Product Type being generated in the scenario. Orders are then processed at the nearest fulfillment point by being batched into a service route.

Once order batches are ready for pickup and delivery, one of the two delivery driver types are requested to serve the delivery route. Drivers are modeled as agents that transition between behavioral states which dictate their activities. A diagram of the basic agent statechart used for the drivers, which shows how they move from point to point along a service route until the final delivery is made, is provided in Figure 9. Upon completion of the service route, the revenue generated from the home delivery requests is calculated as well as the cost of the service. For a dedicated fleet, the service route length from the origin to each customer location and back is calculated and multiplied by the cost per mile parameter. When using a crowdsourced fleet, the number of deliveries is multiplied by the compensation per delivery value. Finally, the profitability of each fleet type, based on the revenue and costs simulated, is written to a database for external analysis.

Validation of the conceptual model refers to ensuring that the underlying logic and assumptions are correct, and that the simulation is reasonable for studying the problem at hand (Sargent 2005; Sargent 2013). Face validity of the conceptual model was achieved through the ongoing dialogue with the company's managers and executives responsible for overseeing the home delivery operations in a series of eight meetings during 2017. Their participation helped ensure that a reasonable, yet realistic conceptualization of real world operations was developed. Further face validity was added by consulting with academics not associated with the research project but experienced in distribution management who confirmed the conceptual model was sufficient.

Computer Model Verification.

After the conceptual validation step, the computer model needed to be verified to ensure that the conceptual model was programmed correctly to achieve intended outcomes (Sargent 2005; Sargent 2013). To ensure the computer model could be verified, it was constructed iteratively in AnyLogic 8.5 where each new addition increased the complexity of the simulation. To verify that the model was working properly, three of Sargent's (2005) techniques were used. First, 2-D animation was used to facilitate the verification process, as order generation, batching, and delivery could each be observed in the AnyLogic software and thus verified to be implemented correctly. Furthermore, because the customers, fulfillment points, and driver agents were plotted in GIS space, animation allowed for observing the delivery process as it would be conducted in real time on actual roads in Staten Island. Next, Degenerate Tests were also conducted to ensure that additions to the model resulted in expected changes in outcomes. For instance, when increasing demand volume between the Product Type variables, there should be greater revenue and cost; this behavior was verified in the model. Finally, Traces were used to follow entities throughout the simulation and verify the proper operations. As agents (orders, customers, fulfillment points, and drivers) transitioned between activities, information about the agent was written to an external log for inspection. The external event log provided evidence that verified that the computer model was implemented correctly. These three techniques collectively verify that the computer model is doing what it is expected to be doing.

Operational and Data Validity.

Operational validity refers to ensuring the model is suitably accurate for its intended purpose by assessing its range of accuracy (Sargent 2005; Sargent 2013). Two techniques were used to assess operational validity: Face validation and examining stochastic variability across simulation runs. Feedback from the managers and experienced academics not associated with the project provided face validity. Stochastic variability across runs in the outcome variable were examined as well, where high variability would imply model inconsistency (Sargent 2005). To examine this variability, 95% confidence intervals (CIs) for the differences in mean monthly profits between fleet types across the four Omnichannel Fulfillment Policy x Product Type interactions were calculated (Balci and Sargent 1984; Sargent 2013). The results, presented in Table 14, indicate the model range of accuracy for each scenario. Since the CIs for the mean differences in monthly profits were relatively narrow compared to the mean differences themselves and do not include values of zero, the model is deemed to have sufficient operational validity.

Data validation refers to ensuring that the data used for distributions and parameters in the model are sufficient and correct. This was achieved using Sargent's (2013) Parameter Variation – Sensitivity Analysis technique where input values are changed and the resulting outputs are examined. Changing the revenue and cost parameters does have an impact on the monthly profitability in each scenario as well as changing the variables. Thus, the data are assumed to be sufficiently valid for this study.

Simulation.

The sample size (N = 1600) for the experimental design was determined using techniques established by Law (2015) and Law and Kelton (1982). Twenty trial runs were performed where the resulting means and variances were used to determine the number of runs per scenario that would allow for a 0.10 relative-precision level in mean monthly profits. The result was that 200 runs were needed for each scenario to allow for proper assessment of steady-state behavior (Law and Kelton 1982). The simulation was built and coded using AnyLogic 8.5 for Windows on an Intel(R) Core™ i5-6500 CPU @ 3.20GHz with 16GB of RAM.

Analysis.

Univariate analysis of variance (ANOVA) was conducted on the three predictor variables (Omnichannel Fulfillment Policy, Product Type, and Fleet Type) to examine the individual variable effects, two-way interactions, and the three-way interaction on the lone outcome variable (Monthly Profitability). Graphical inspection of the results determined that the assumption of normality in the outcome variable was not violated. The assumption of heterogeneity of variance was examined using Hartley's F_{max} test (Pearson and Hartley 1954), rather than Levene's (1960) test because, much like the KS test, Levene's is also overly sensitive to large sample sizes. Hartley's variance ratio was calculated between fleet types for each Fulfillment Policy x Product Type interaction with a sample size of 200. All four variance ratios exceeded the critical value of 1.0 at N=200, indicating that the data do not violate the assumption of homogeneity of variance.

Results.

The descriptive statistics and results of the ANOVA are presented in Tables 15 and 16, respectively. While the individual variable and two-way interaction effects on monthly profitability were calculated, only the three-way interaction is focused on in this results discussion (see Figure 10 for the three-way interaction plot). The ANOVA showed that there are statistically significant differences in profitability of the two Fleet Types when different Fulfillment Policies are implemented to deliver different Product Types. In all cases, the crowdsourced fleet was more profitable than the dedicated fleet to make home deliveries. This is a somewhat expected result because crowdsourced drivers are compensated on a per-delivery basis, not a per-mile basis like dedicated drivers. So, when service routes become longer, it's more cost-effective for the shipper to crowdsource the deliveries.

Looking at the differences between product types, a crowdsourced fleet is more profitable when delivering functional, rather than innovative products, where demand volume is greater (see Table 15 for means). This finding aligns with previous research suggesting that crowdsourced logistics is likely best used to deliver functional products with low values (Castillo et al. 2017). The results also suggest that when using a crowdsourced fleet, the choice of fulfillment policy may be less critical. In other words, when crowdsourcing delivery, the most meaningful differences in profitability under each fulfillment policy occur between functional and innovative products, not between fulfillment policies (see Figure 10). This is also explained by the per-delivery compensation structure of crowdsourced logistics.

When considering profitability of a dedicated fleet, the results are a little more nuanced. A SFS policy is more profitable than a SFDC policy because the retail stores are physically closer to the end customer. Thus, the distance traveled by dedicated drivers in a SFS policy will be lower on average compared with those distances under SFDC. When delivering functional products, demand volume is greater than with innovative products (Fisher 1994), so any profit improvements or cost increases will be amplified. This explains why it is more profitable to deliver functional products (M = \$544.39) than innovative products (M = \$174.11) under a SFS policy, but it is costlier to deliver functional products (-\$2151.11) than innovative ones (-\$1473.22) under a SFDC policy.

Taking these results collectively, it appears that crowdsourcing delivery may be more profitable than using a dedicated logistics fleet. Stated differently, it is cheaper to operate crowdsourced logistics than a dedicated fleet. However, because crowdsourced drivers are amateurs without much or any experience who manage their own delivery acceptance rates, the reliability of a crowdsourced fleet in terms of logistics service quality is lower than it is for a dedicated fleet (Castillo et al. 2017). So, while it may be initially enticing to crowdsource home delivery because of the lower costs, the lower customer service reliability, in addition to other risks, may not be worth it for some shippers. This tradeoff between cost and customer service is examined more deeply in Study 2.

Study 2 – Logistics Cost-Service Tradeoffs in Hybrid Delivery Fleets

Study 2 employs Simulation Optimization (SO) to examine the cost-service tradeoff when using a hybrid fleet of drivers for same day delivery. SO is a stochastic optimization method where an objective function is sought to be optimized subject to a system of stochastic parameters and constraints (Carson and Maria 1997; April et al. 2003; Klassen and Yoogalingam 2009; Amaran et al. 2015). In SO, the objective function and parameters are estimated through simulation (Fu et al. 2005; Klassen and Yoogalingam 2009). The strength of SO lies in its application of metaheuristics to quickly search a large, multidimensional solution space to find a near-optimal combination of decision variables in the simulation that satisfies the stochastic objective function and constraints (Law 2015).

This study extends Study 1 by adding on-demand same day delivery operations to the scheduled home delivery service. Previous research has suggested that crowdsourced drivers may be best used as excess capacity in a hybrid delivery fleet comprised of a mix of dedicated and crowdsourced drivers, rather than as a sole delivery option (Castillo et al. 2017). Thus, the goal of this study is to apply SO to the problem of sizing hybrid delivery fleets and gain insight into how that decision is affected by last mile logistics strategy (in terms of a minimize cost or maximize responsiveness strategy, Omnichannel Fulfillment Policy, and Product Types) and the costs for the two fleet types.

Simulation Model.

The simulation model is similar to Study 1 with four changes. First, in addition to scheduled home delivery routes being served daily, same day deliveries where orders are received dynamically and stochastically throughout the day are also made. To simulate this, a second discrete event process was added to each fulfillment point agent to sort between scheduled and same day delivery requests. Rather than only receiving a small number of orders each day at one point in time, customers continue to place orders for same day delivery throughout the day in accordance with a Poisson distribution with $\lambda = 3$ orders per hour (for innovative products; $\lambda = 6$ for functional products). After sorting the orders based on delivery urgency, they await availability of one of the driver agent types for pickup and delivery.

The second change to the simulation model concerns dedicated driver agents and how they behave with regards to picking up orders (see Figure 11). In Study 2, it is assumed that only dedicated drivers serve scheduled delivery routes and crowdsourced drivers are used when demand exceeds the delivery capacity of the dedicated fleet. At the beginning of each day, dedicated drivers assigned to each store pickup and service that day’s customer route. Upon completion, the dedicated driver returns to the store and is made available for conducting same day deliveries. Both dedicated and crowdsourced driver types conduct same day delivery services, but dedicated driver types are preferred when they're available. If they're busy, then the store requests a crowdsourced delivery agent to make the same day delivery, simulating the role of crowdsourcing as excess delivery capacity. Upon completion of each delivery, the total cost of delivery is calculated using a factor ranging from $1 per mile to $5 per mile.

The third change deals with the crowdsourced delivery agent behavior. The statechart is presented in Figure 11 as well. Crowdsourced drivers begin the day in the vicinity of a retail store and await an offer for a pickup and delivery. The rate at which a crowdsourced driver decides to accept the delivery is determined by the compensation amount set at the beginning of each run. This per delivery cost ranges from $1 where a driver only accepts deliveries 10% of the time to $7 where the acceptance rate rises to 100%. If a crowdsourced driver decides to reject a delivery request, then it enters a loop where it moves between random places to simulate the autonomy it has over its schedule. This continues until it randomly ejects the loop and returns to the retail store to decide to accept or reject another delivery. When the compensation amount is low, the acceptance rate is also low, thus, it can be expected that delivery capacity and thus lead times would be negatively affected.

Finally, two new outcome variables were needed to assess the cost-service tradeoff in a hybrid fleet of delivery vehicles. System Cost refers to the total delivery costs at the system level (i.e. all delivery operations on Staten Island) for operating the hybrid fleet to conduct both scheduled and same day delivery services. It is calculated based on the empirical cost parameters for each fleet type. System Average Order Fulfillment Time, the time difference between when a request for same day delivery is received and when the order is delivered, is also introduced and measures responsiveness where lower lead times corresponds to better logistics customer service.

Problem Description.

The optimization was set up to minimize either System Cost (C_{SYS}) or System Average Order Fulfillment Time (OFT_{SYS}), resulting in two separate problems with different objective functions being used depending on the overarching logistics strategy (i.e. minimize cost or maximize responsiveness). The objective functions are sought by manipulating two decision variables until a near-optimal combination is found through the scatter search algorithm: the Number of Dedicated Drivers per Store (N_{DED}), where $1 \leq N_{DED} \leq 5$, and the Number of Crowdsourced Drivers per Store (N_{CS}), where $1 \leq N_{CS} \leq 10$. Since this is an explorative research effort, the number of dedicated (crowdsourced) drivers is constrained to 5 (10) per store. It is assumed that only dedicated drivers conduct scheduled delivery routes and that a hybrid fleet comprised of both driver types perform the same day deliveries (although, dedicated drivers are preferred when they're available). The costs for each fleet type are defined as a set of parameters: dedicated fleet cost ($) per mile, C_{DED} = {1, 2.50, 5}, and crowdsourced fleet cost ($) per delivery, C_{CS} = {1, 3, 7}, where the crowdsourced driver acceptance rate, AR_{CS}, is estimated by the probabilistic distribution in Figure 11. The objective functions are optimized under each cell of a 2x2 experimental design: Omnichannel Fulfillment Policy, *OFP* = {SFS, SFDC} and Product Types, *PT* = {Innovative, Functional}.

Validation.

Validation of the solution quality is critical since there are many possible configurations resulting from the stochasticity present in the simulation model. One common method of validating solution quality is to compare results to that of previous studies, but since this is the first SO examining the cost-service tradeoff when using crowdsourced delivery, no previous studies exist to refer to. However, the scatter search metaheuristic ensures that the highest quality solutions are found by strategically exploring the global solution space using evolutionary mechanisms and path relinking, rather than a randomized search (Glover et al. 2000; Martí et al. 2006; Amaran et al. 2015). The stochasticity in the simulation could also raise concerns about solution quality since multiple runs of each scenario would produce different outputs due to randomness. To mitigate this concern, *n* replications are used in each scenario of the experimental design in the optimization, where $n = 20$ to maintain a relative-precision level of 0.10 in the outputs (Law 2015). Thus, C_{SYS} and OFT_{SYS} outputs are estimated as the average outputs across twenty replications of each scenario. Taken together, the use of scatter search and replications in the simulation provide sufficient validation of the optimization's solution quality.

Results.

The results of the fleet mix problem based on logistics strategy, omnichannel fulfillment policy, product type, and fleet type cost are depicted in Figures 12 and 13 and reported in Table 17. These charts show how the cost-service tradeoff changes in terms of system level costs per month, average order fulfillment times, and hybrid fleet sizes and mixes based on how the costs of dedicated and crowdsourced fleets change.

Figure 12 shows the tradeoffs when a “Minimize Cost” logistics strategy is employed. Overall, the results suggest that to achieve minimal delivery costs in the system, fleet sizes should be as small as possible. This is somewhat expected since with fewer drivers to pay, the incurred costs are lower for the system. The smaller fleet sizes are more common under SFDC than under SFS, implying that with a single DC to fill same day deliveries from, the optimal hybrid fleet size and mix that minimizes cost is one of each driver type. While total delivery costs might be low under SFDC because of the small fleet sizes, the average order fulfillment times are such that same day deliveries aren’t able to be conducted, thus harming logistics customer service. This is consistent between innovative and functional products as well.

Under a minimize cost strategy employing a SFS fulfillment policy, the fleet mix and sizes are more discernably affected by fleet costs. In most cases where the dedicated drivers cost less than crowdsourced, the optimal fleet mix favors dedicated driver types by as much as a 5:1 ratio with fleet sizes of six total drivers (e.g. at the $1/$7 or $2.5/$7 dedicated to crowdsourced fleet cost ratios). The optimal fleet sizes generally remain small (i.e. two drivers, one of each type) however, if dedicated costs exceed crowdsourced costs (e.g. at $2.5/$1 or $5/$1). Overall, as fleet costs increase, the cost-service tradeoff becomes more severe, where it is more expensive to offer faster delivery service. This is generally true across product types as well.

One interesting point in Figure 12 that stands out from the general trends occurs at the \$5/\$3 fleet cost ratio in the SFS x Innovative quadrant, where the fleet size is large (11 vehicles) and has a 1:10 fleet mix ratio. One possible explanation for this is that at \$3 per delivery, crowdsourcing is still cheap enough that a crowdsourced-heavy hybrid fleet can be used to make deliveries at a minimal cost compared to a dedicated-heavy hybrid fleet at \$5 per mile. This implies that in practice, if fuel, labor, and other costs associated with dedicated fleets increase while crowdsourced costs remain stable, crowdsourcing delivery could be a feasible means of maintaining responsiveness while keeping costs low.

Figure 13 presents the cost-service tradeoffs at varying fleet costs, fulfillment policies, and product types under a Maximize Responsiveness strategy. Overall, to minimize lead times, fleet sizes should be as large as possible to maximize delivery capacity. Most fleet sizes are at the upper bounds of the constraints, five dedicated and ten crowdsourced drivers per store, and reflect a 1:2 dedicated-to-crowdsourced fleet mix ratio. SFDC appears to be the more expensive fulfillment policy for same day delivery with a hybrid fleet than SFS. For instance, at the empirical fleet cost ratio of \$2.5/\$3, it will cost around \$17,000 per month to be able to provide about 5-hour delivery service, for both functional and innovative products. A SFS fulfillment policy at the same fleet costs can be expected to cost around \$10,000 to provide ~2-hour delivery service.

However, not all fleet sizes should be maximized under a SFS policy to maximize responsiveness. For instance, when the cost of crowdsourcing is low, the fleet size should be relatively small (six drivers) and be comprised of mostly dedicated drivers (e.g. at the $1/$1, $2.5/$1, $5/$1 cost ratios). This is somewhat unexpected since at first glance, a retailer may desire to acquire as many crowdsourced drivers as possible since they operate at a lower cost. This is ill advised though, because when crowdsourced drivers' remuneration is low, their delivery acceptance rates will also be low, which in turn harms average order fulfillment times. Thus, when using SFS where more delivery capacity is needed, it's advisable to pay crowdsourced drivers more to maximize responsiveness.

Taken together, Figures 12 and 13 show how the hybrid delivery fleet size and mix change along with the logistics cost-service tradeoff between Minimize Cost and Maximize Responsiveness logistics strategies as fleet costs change. It is somewhat expected that smaller fleet sizes correspond with lower total delivery costs and larger fleet sizes with higher responsiveness. Additionally, that SFS generally results in better responsiveness than SFDC is also expected, since the fulfillment points are closer to customer locations. However, under a Minimize Cost strategy, the difference in delivery costs between SFS and SFDC is not as discernible, which is likely explained by the added distances from a single DC being offset by the greater number of drivers needed in SFS. This is different from a Maximize Responsiveness strategy, where delivery costs are generally lower under SFS than SFDC. The higher SFDC costs in Maximize Responsiveness are likely a result of the longer distances to be traveled, considering that fleet sizes are mostly as large as possible in this logistics strategy.

To facilitate deeper understanding of the differences in the cost-service tradeoff between logistics strategies when making same day delivery with a hybrid fleet, scatter plots were generated showing the cost-lead time relationship at each fleet cost combination (see Figure 14). The two charts on the left of Figure 14 demonstrate that under a SFDC fulfillment policy, the tradeoff between cost and service is heavily affected by the overarching logistics strategy. Under a Minimize Cost strategy when using SFDC, for both product types, same day delivery is not possible, although system costs are relatively low. This is likely because minimizing system delivery costs requires minimizing the fleet size, so there is less capacity available to make deliveries.

When looking at SFS fulfillment policies however, there are some scenarios where the cost-service tradeoff between logistics strategies is relatively small, implying that responsive delivery can be performed at a relatively low cost using a hybrid delivery fleet, and appears to be true for both product types. This finding is somewhat counter-intuitive and interesting because generally speaking, cost and responsiveness are positively associated. The charts on the right of Figure 14 suggest there are fleet cost scenarios where switching from a Minimize Cost to Maximize Responsiveness can result in improved responsiveness either with a small increase in cost or even reduced cost. Specifically, comparing the SFS policies for functional and innovative products in Table 17 at the empirical fleet cost ratios (i.e. $2.5/$3) shows that switching from cost minimization to responsiveness maximization logistics strategy results in a 13.23% cost increase but a 96.32% responsiveness increase for functional products. For innovative products, switching actually results in a 0.81% cost decrease for a gain of 86.62% in responsiveness. Thus, using a hybrid delivery fleet for same day delivery under a SFS fulfillment policy has potential to be the best balance of cost and service.

These results and discussion provide evidence of how the logistics cost-service tradeoff in a hybrid delivery fleet is impacted by the overarching logistics strategy, omnichannel fulfillment policy, and product characteristics to provide insight into how crowdsourcing can be used for same day delivery.

Discussion and Conclusions

This research effort developed and applied an empirically grounded simulation optimization model to examine several research questions related to the use of crowdsourced delivery in last mile logistics. Combining simulation and analytical methods grounded in empirical data strengthens the link between theoretical rigor and managerial relevance of this research (Klassen and Yoogalingam 2009). Overall, this research has three major findings regarding the financial and operational performance of crowdsourced logistics for last mile delivery.

First, Study 1 provided insight into the profitability differential between crowdsourced and dedicated logistics. The results showed that crowdsourced logistics is generally more profitable than dedicated logistics for home delivery. Stated differently, crowdsourced delivery is less costly to operate than dedicated delivery, but the added cost benefit comes at lower service quality and higher risks, since there is more uncertainty in the reliability of what is essentially a fleet of amateur drivers (Castillo et al. 2017). Study 1 also suggests that shipping functional products directly from storefronts can be more profitable with a crowdsourced fleet than with a dedicated fleet. Additionally, it appears that the choice of omnichannel fulfillment policy might not be as critical when crowdsourcing home deliveries, since the cost incurred from crowdsourcing is not as dependent on the distance traveled by the driver.

Second, Study 2 examined a hybrid delivery fleet for same day delivery comprised of both dedicated and crowdsourced drivers. The goal was to explore how fleet sizing and mix are impacted by fleet costs, fulfillment policies, product types, and logistics strategy in terms of minimizing cost or maximizing responsiveness. It is not surprising to find that to minimize costs, fleet sizes should be as small as possible because fewer delivery costs are incurred with fewer drivers. Conversely, to maximize responsiveness, larger fleet sizes are needed. However, it is interesting to note that the fleet mix ratios of dedicated-to-crowdsourced drivers varies as well depending on the logistics strategy and fulfillment policy. When minimizing cost, predominantly dedicated hybrid fleets are favorable for last mile delivery, specifically if dedicated delivery costs per mile are low. This isn’t necessarily the case with crowdsourced drivers though. When crowdsourced driver remuneration is low, the driver acceptance rate remains low as well, thus, the ability to perform same day deliveries is diminished.

Lastly, Study 2 also explored the last mile logistics cost-service tradeoff when using a hybrid fleet of delivery drivers. Generally, under a Minimize Cost strategy, it is more expensive to provide same day delivery services, a somewhat anticipated finding. It can also be expected that conducting same day delivery with a hybrid fleet under a Minimize Cost strategy will be extremely difficult, especially if a SFDC strategy is used. In fact, the results showed that SFDC in a minimize cost strategy is not able to achieve same day deliveries, irrespective of the product type and fleet costs. A SFS policy is more likely to be able to provide same day delivery with a hybrid fleet at a minimal cost however, provided that dedicated fleet costs remain low and that crowdsourced fleet rates are high enough to ensure a high acceptance rate. Under a Maximize Responsiveness strategy, a somewhat counter-intuitive trend was found. It was anticipated that as responsiveness increases, so too would cost, but the results showed an opposite trend: as responsiveness increases, there are certain scenarios in which costs can be decreased. Most prominently, when conducting same day delivery under a SFS policy. This finding aligns with the major finding of Study 1 as well as previous research suggesting that crowdsourced logistics may be best suited for delivering low cost products with predictable demand (Castillo et al. 2017).

Limitations and Future Research.

The results reveal how hybrid delivery fleets can be used for same day delivery and what can be expected in terms of financial and operational performance. While Staten Island was chosen for this project because it offered a relatively simple and somewhat isolated network in which to simulate and optimize delivery operations, future research should consider the effect of denser geographic areas. For instance, the population density of Brooklyn and Manhattan greatly exceeds that of Staten Island. With higher density customer networks, greater route efficiencies can be achieved with implications for both financial and operational performance (Boyer, Prud'homme, and Chung 2009).

In this research, the cost parameters for a crowdsourced delivery fleet were set at the beginning of each simulation run, so they were essentially static for the duration of the simulation. While this isn't a problem per se for the results of the current research, one opportunity for future efforts is to consider the effect of dynamic pricing strategies (i.e. "price surging") on the delivery acceptance rate and subsequent financial or operational performance.

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scalable solutions." *Transportation Research Part E: Logistics and Transportation Review.* 93:279-93. doi: 10.1016/j.tre.2016.06.002.

Appendix – Figures and Tables

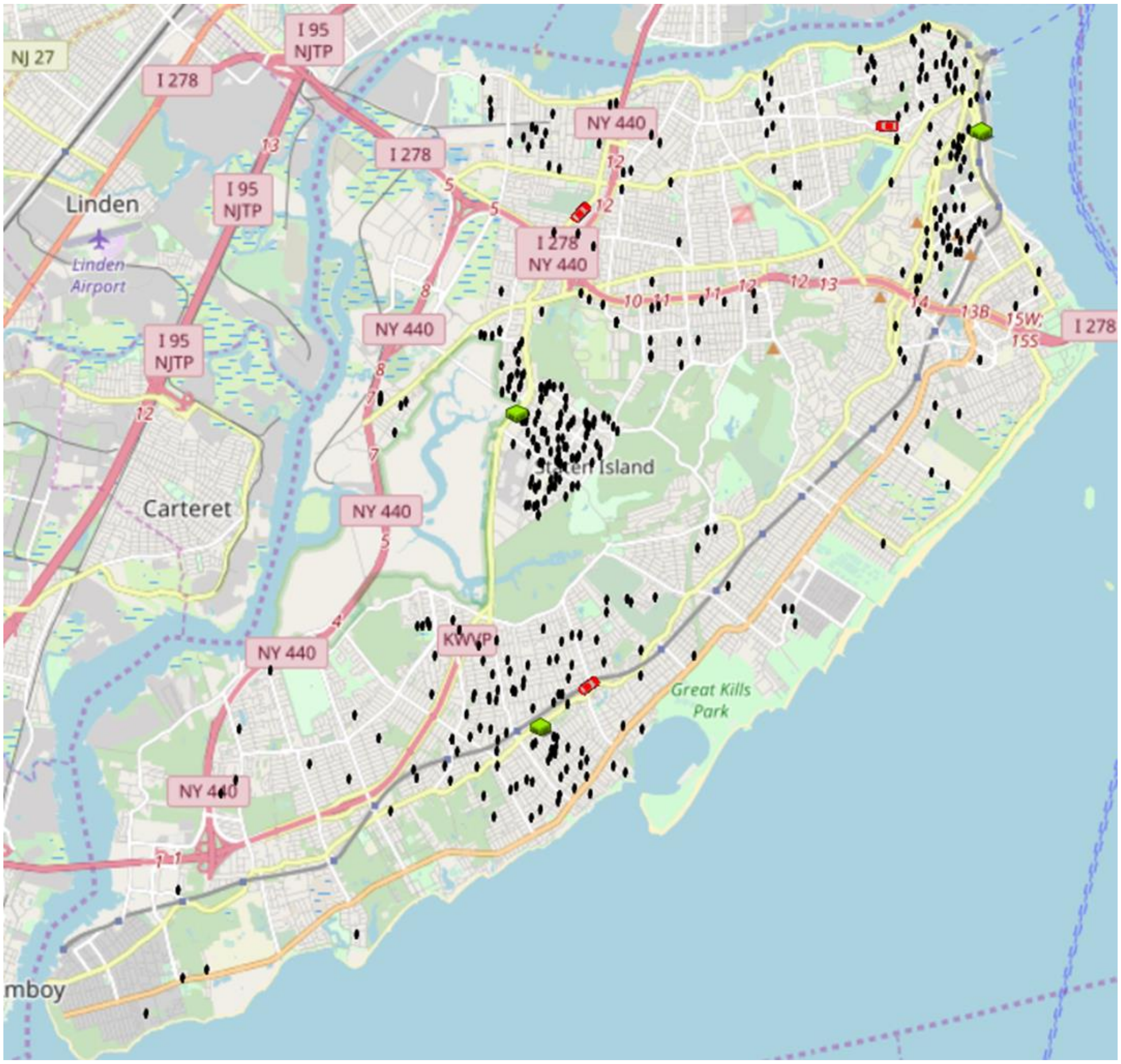

Figure 7 - Customer Network & Simulation Screenshot

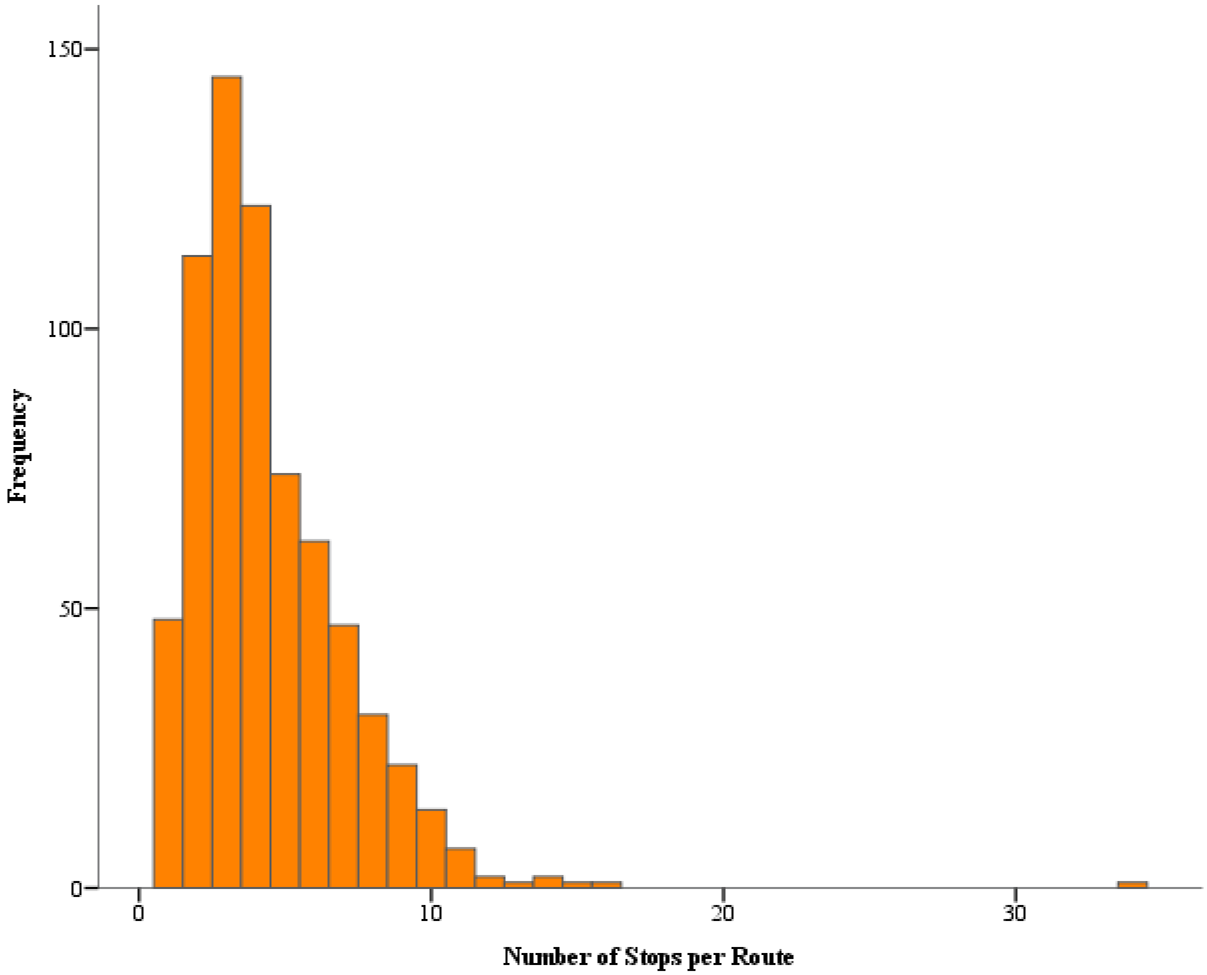

Figure 8 - Delivery Data Empirical Distribution

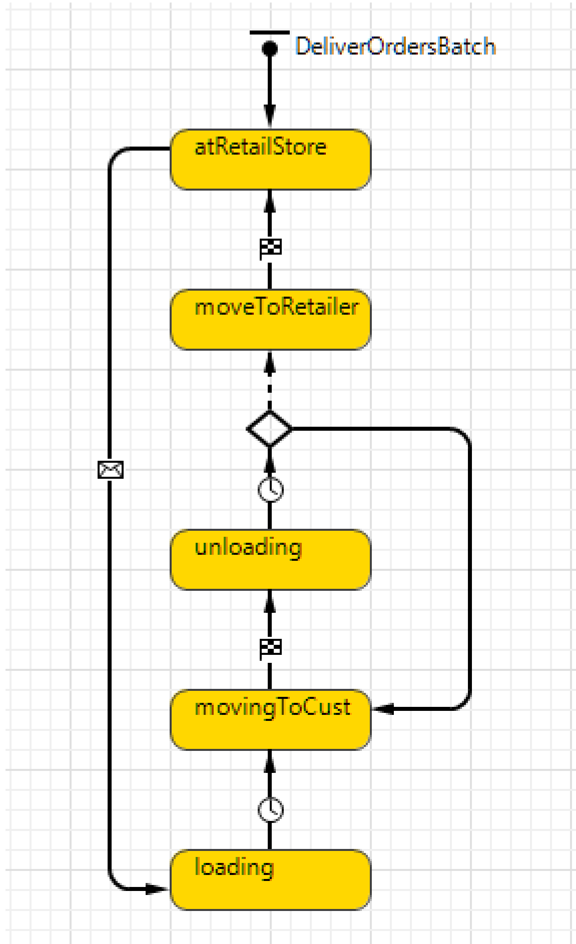

Figure 9 - Study 1 Delivery Agent Statechart

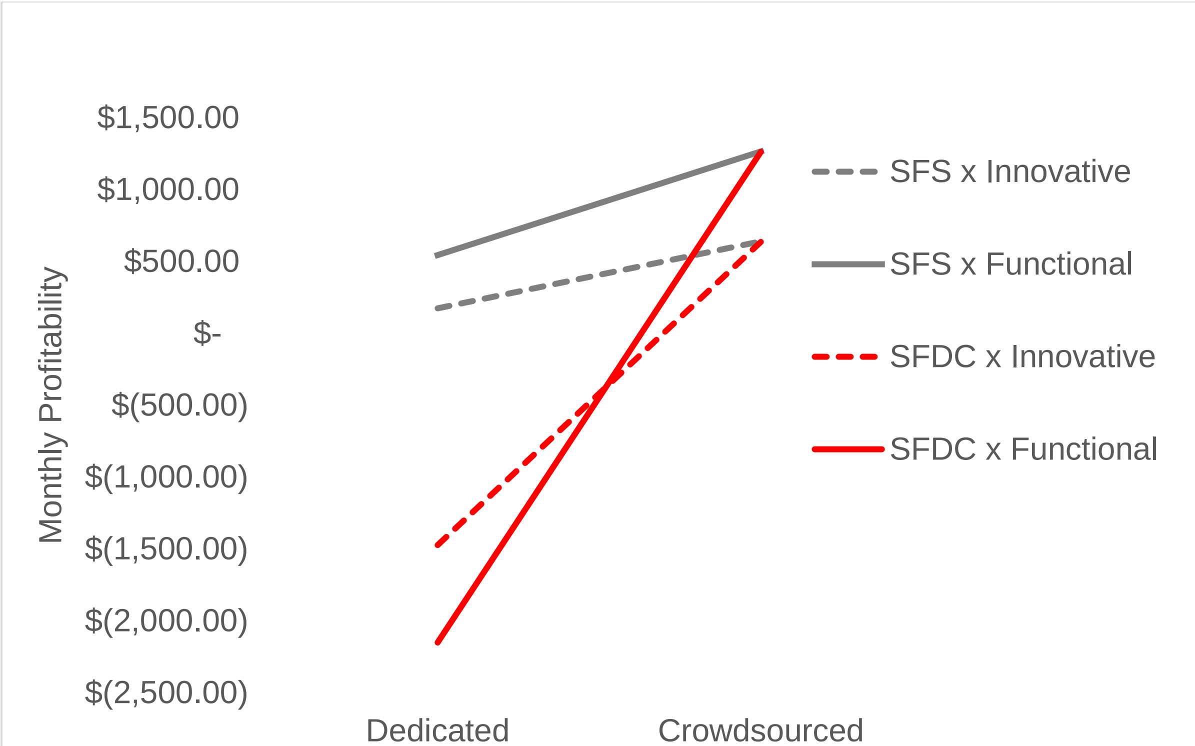

Figure 10 - Three Way Interaction Plot for Scheduled Home Deliveries

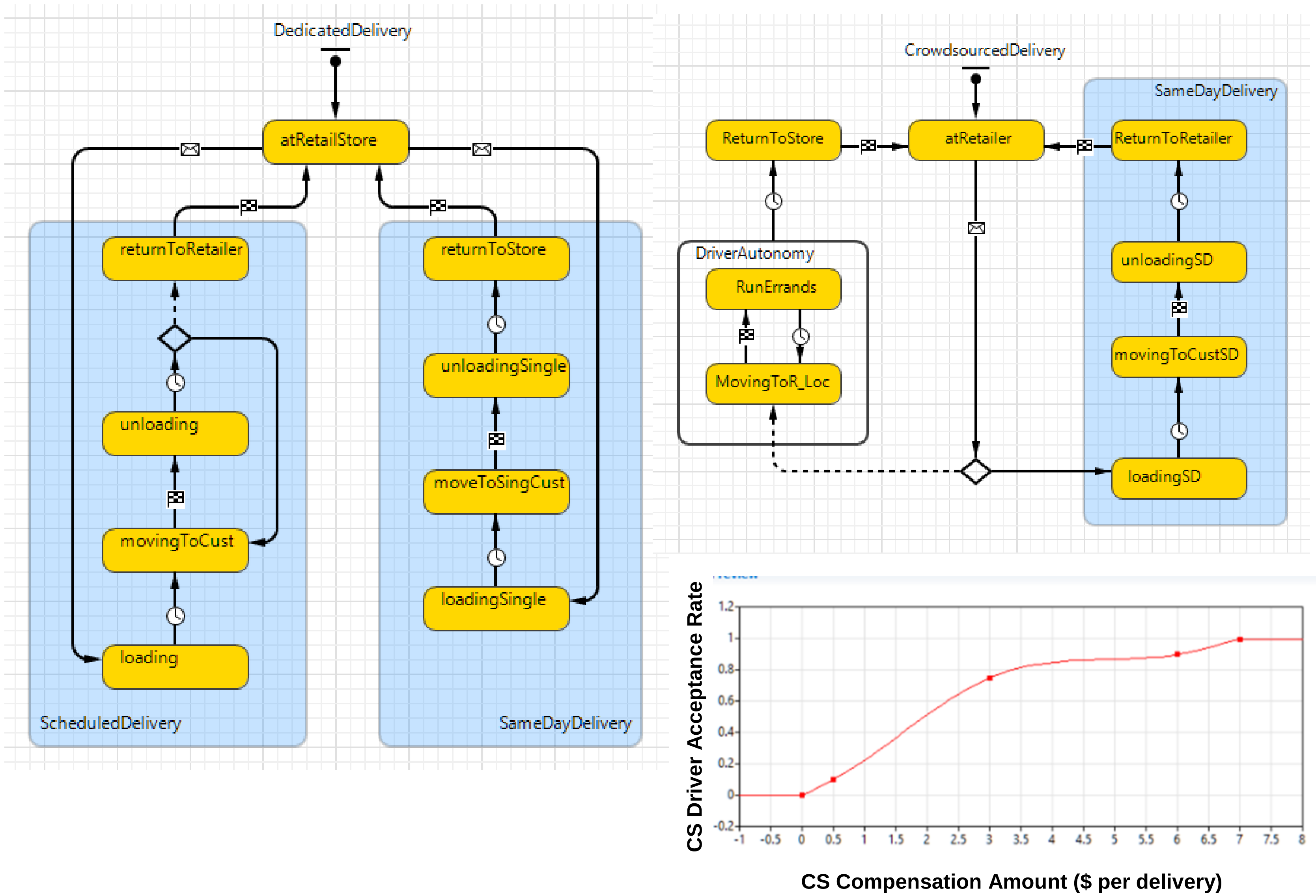

Figure 11 - Driver Agent Statecharts for Simulation Optimization

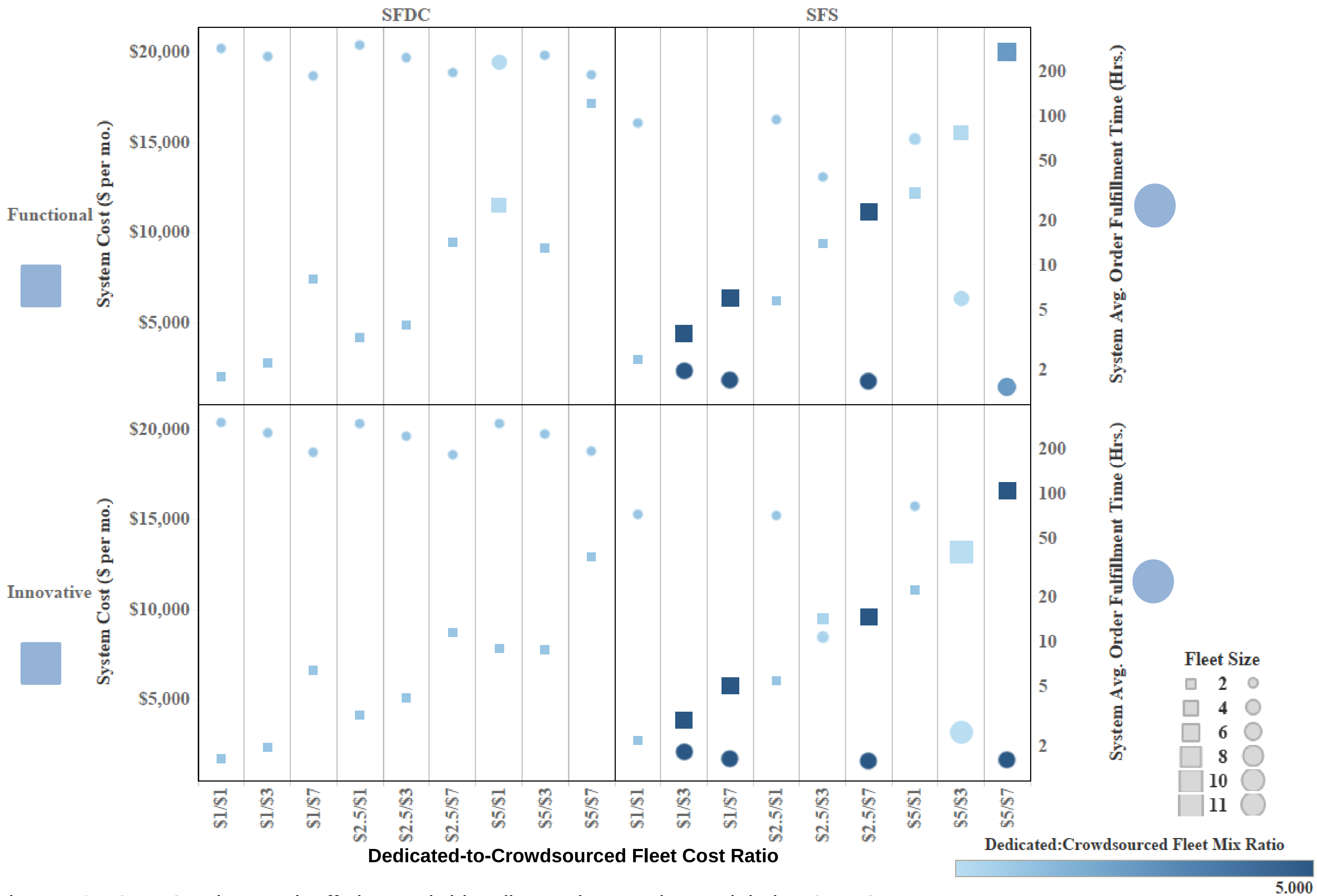

Figure 12 - Cost-Service Tradeoffs in a Hybrid Delivery Fleet Under a Minimize Cost Strategy

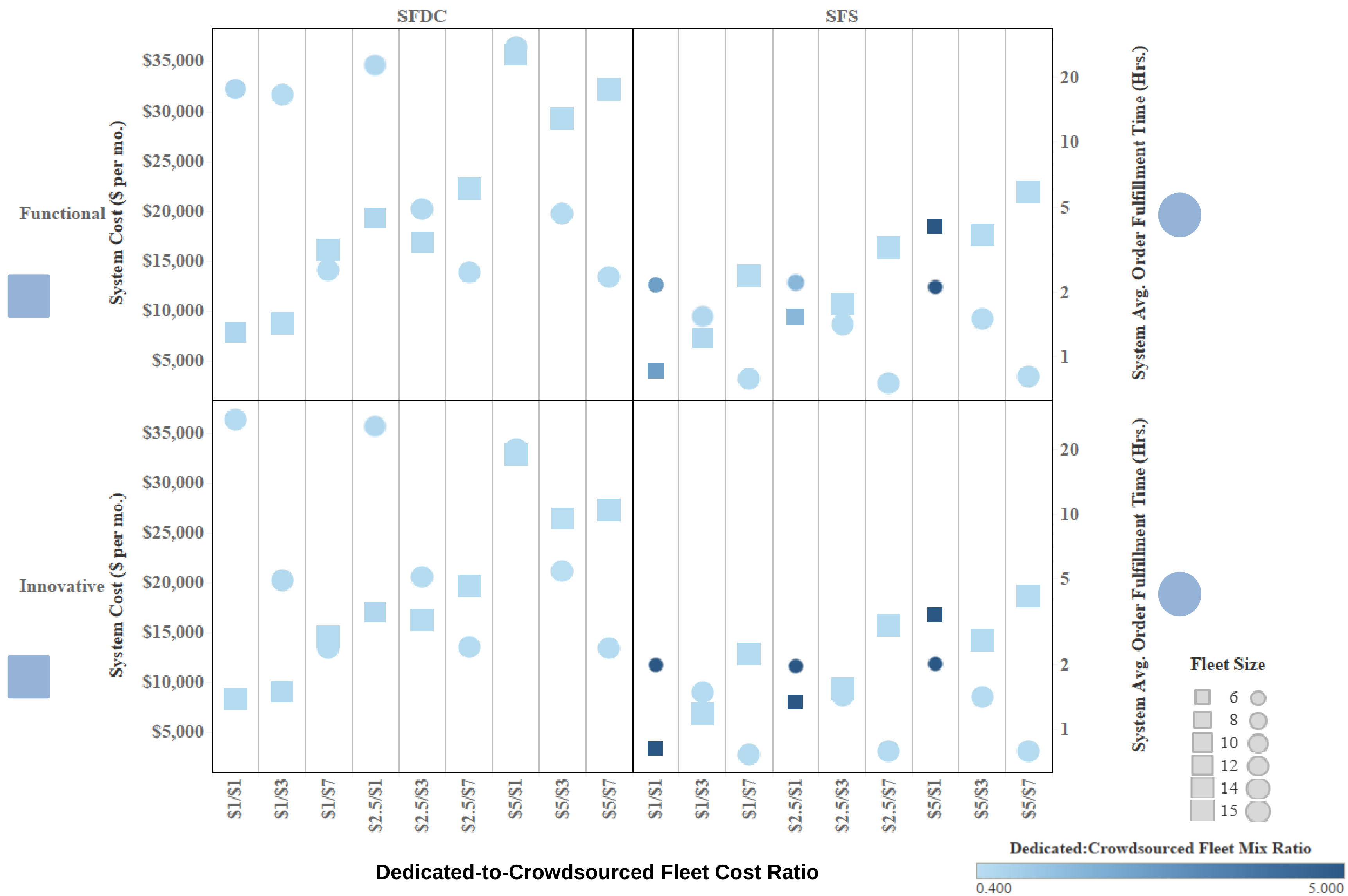

Figure 13 - Cost-Service Tradeoffs in a Hybrid Delivery Fleet Under a Maximize Responsiveness

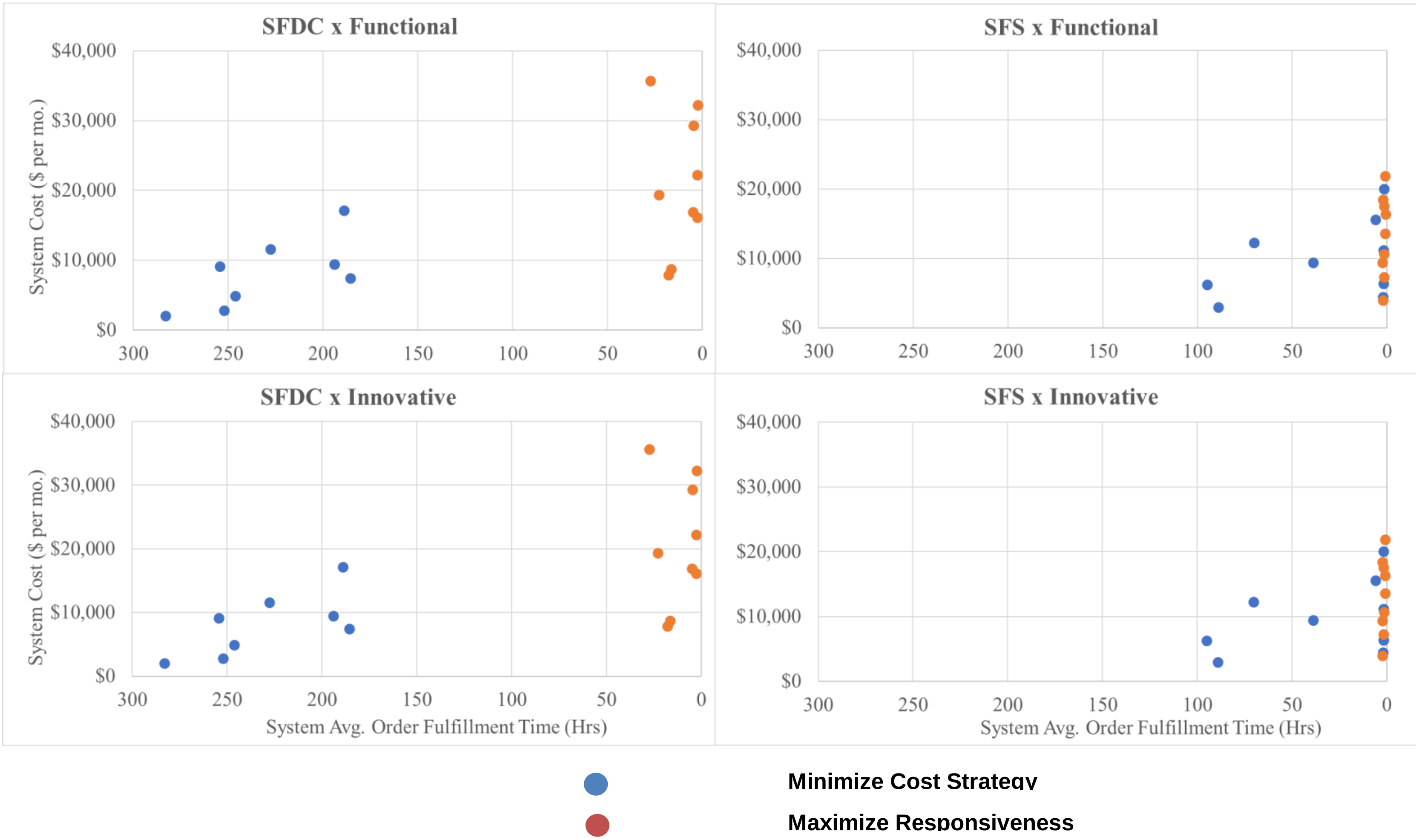

Figure 14 - Comparing Cost-Service Tradeoffs Between Logistics Strategies in Same Day Delivery with a Hybrid Fleet

Table 14 - Operational Validity Test for Study 1

Fulfillment Policy x Product Type Interaction	**Mean Difference in Monthly Profit between Fleet Types**	**t-stat**	**df**	**p-val**	**95% CI of the Difference in Means**
SFS x Innovative	$465.74	143.76	398	<0.001	($459.37, $472.10)
SFS x Functional	$721.01	127.50	398	<0.001	($709.89, $732.12)
SFDC x Innovative	$2,109.49	274.09	398	<0.001	($2094.36, $2124.63)
SFDC x Functional	$3,414.08	167.77	398	<0.001	($3374.07, $3454.09)

Table 15 - Descriptive Statistics for Three-Way Interaction

Fleet Type	Dedicated				Crowdsourced			
Fulfillment Policy	Ship from Store		Ship from DC		Ship from Store		Ship from DC	
Product Type	Innovative	Functional	Innovative	Functional	Innovative	Functional	Innovative	Functional
Mean Profit per Month	$174.11	$544.39	-$1,473.22	$2,151.11	$639.85	$1,265.40	$636.27	$1,262.97
SD	$29.61	$48.80	$92.41	$260.05	$34.96	$63.35	$57.52	$123.29
95% CI	($169.99, $178.24)	($537.59, $551.20)	(-$1486.11, -$1460.34)	(-$2187.37, -$2114.85)	($634.98, $644.72)	($1256.57, $1274.23)	($628.25, $644.29)	($1245.78, $1280.16)

Note: N=1600

Table 16 - ANOVA Results for Study 1

Source	df	F	Sig.
Intercept	1	138,082.71	0.000
Omnichannel Fulfillment Policy	1	4,743.77	0.000
Product Type	1	17,176.96	0.000
Fleet Type	1	67,973.06	0.000
OFP x PT	1	1,108.44	0.000
OFP x FT	1	4,607.17	0.000
PT x FT	1	5,938.97	0.000
OFP x PT x FT	1	1,121.20	0.000

R Squared = 0.985

Table 17 - Simulation Optimization Results

				Minimize Cost Strategy				Maximize Responsiveness Strategy				Percent Difference Between Strategies	
C_{DED}	C_{CS}	OFP	PT	C_{SYS}	OFT_{SYS}	N_{DED}	N_{CS}	C_{SYS}	OFT_{SYS}	N_{DED}	N_{CS}	C_{SYS}	OFT_{SYS}
$ 1.00	$ 1.00	SFDC	Functional	$1,975	$283	1	1	$7,850	$18	5	7	-297%	94%
$ 1.00	$ 3.00	SFDC	Functional	$2,750	$252	1	1	$8,707	$16	5	10	-217%	93%
$ 1.00	$ 7.00	SFDC	Functional	$7,411	$186	1	1	$16,105	$3	5	10	-117%	99%
$ 2.50	$ 1.00	SFDC	Functional	$4,139	$301	1	1	$19,339	$23	5	8	-367%	92%
$ 2.50	$ 3.00	SFDC	Functional	$4,854	$246	1	1	$16,847	$5	5	9	-247%	98%
$ 2.50	$ 7.00	SFDC	Functional	$9,420	$194	1	1	$22,177	$2	5	10	-135%	99%
$ 5.00	$ 1.00	SFDC	Functional	$11,541	$228	1	4	$35,650	$27	5	9	-209%	88%
$ 5.00	$ 3.00	SFDC	Functional	$9,104	$254	1	1	$29,244	$5	5	10	-221%	98%
$ 5.00	$ 7.00	SFDC	Functional	$17,132	$189	1	1	$32,235	$2	5	10	-88%	99%
$ 1.00	$ 1.00	SFS	Functional	$2,954	$89	1	1	$3,927	$2	5	2	-33%	98%
$ 1.00	$ 3.00	SFS	Functional	$4,415	$2	5	1	$7,263	$2	5	8	-65%	20%
$ 1.00	$ 7.00	SFS	Functional	$6,340	$2	5	1	$13,551	$1	5	10	-114%	53%
$ 2.50	$ 1.00	SFS	Functional	$6,221	$95	1	1	$9,344	$2	5	3	-50%	98%
$ 2.50	$ 3.00	SFS	Functional	$9,372	$39	1	1	$10,612	$1	5	10	-13%	96%
$ 2.50	$ 7.00	SFS	Functional	$11,141	$2	5	1	$16,323	$1	5	10	-47%	54%
$ 5.00	$ 1.00	SFS	Functional	$12,209	$70	1	2	$18,403	$2	5	1	-51%	97%
$ 5.00	$ 3.00	SFS	Functional	$15,535	$6	1	4	$17,538	$2	5	10	-13%	75%
$ 5.00	$ 7.00	SFS	Functional	$19,998	$2	5	2	$21,880	$1	5	10	-9%	46%

Table 17 Continued

				Minimize Cost Strategy				Maximize Responsiveness Strategy				Percent Difference Between Strategies	
C_{DED}	C_{CS}	OFP	PT	C_{SYS}	OFT_{SYS}	N_{DED}	N_{CS}	C_{SYS}	OFT_{SYS}	N_{DED}	N_{CS}	C_{SYS}	OFT_{SYS}
$ 1.00	$ 1.00	SFDC	Innovative	$1,672	$297	1	1	$8,330	$27	5	10	-398%	91%
$ 1.00	$ 3.00	SFDC	Innovative	$2,325	$253	1	1	$9,083	$5	5	9	-291%	98%
$ 1.00	$ 7.00	SFDC	Innovative	$6,606	$189	1	1	$14,558	$2	5	10	-120%	99%
$ 2.50	$ 1.00	SFDC	Innovative	$4,120	$293	1	1	$17,116	$26	5	8	-315%	91%
$ 2.50	$ 3.00	SFDC	Innovative	$5,041	$240	1	1	$16,211	$5	5	10	-222%	98%
$ 2.50	$ 7.00	SFDC	Innovative	$8,722	$181	1	1	$19,625	$2	5	10	-125%	99%
$ 5.00	$ 1.00	SFDC	Innovative	$7,805	$293	1	1	$32,827	$20	5	10	-321%	93%
$ 5.00	$ 3.00	SFDC	Innovative	$7,743	$252	1	1	$26,409	$5	4	10	-241%	98%
$ 5.00	$ 7.00	SFDC	Innovative	$12,918	$190	1	1	$27,263	$2	5	10	-111%	99%
$ 1.00	$ 1.00	SFS	Innovative	$2,722	$72	1	1	$3,367	$2	5	1	-24%	97%
$ 1.00	$ 3.00	SFS	Innovative	$3,803	$2	5	1	$6,815	$1	5	10	-79%	18%
$ 1.00	$ 7.00	SFS	Innovative	$5,723	$2	5	1	$12,866	$1	5	10	-125%	53%
$ 2.50	$ 1.00	SFS	Innovative	$6,044	$71	1	1	$8,074	$2	5	1	-34%	97%
$ 2.50	$ 3.00	SFS	Innovative	$9,448	$11	1	2	$9,371	$1	5	10	1%	87%
$ 2.50	$ 7.00	SFS	Innovative	$9,564	$2	5	1	$15,654	$1	5	10	-64%	49%
$ 5.00	$ 1.00	SFS	Innovative	$11,075	$81	1	1	$16,777	$2	5	1	-51%	98%
$ 5.00	$ 3.00	SFS	Innovative	$13,163	$2	1	10	$14,236	$1	5	10	-8%	42%
$ 5.00	$ 7.00	SFS	Innovative	$16,564	$2	5	1	$18,651	$1	5	10	-13%	51%

V. CONCLUSIONS

This dissertation contained three essays that studied emergent crowdsourcing phenomenon in logistics and supply chain management. The purpose of this dissertation was to explore the implications of incorporating Crowdbased Logistics Business Models (CLBM) into omnichannel supply chain strategy and understand how they impact competitive advantage. Before assessing how CLBMs affect competitive advantage (in terms of financial performance), it is necessary to understand how they fit into current strategy and the operational performance implications. To make sense of how CLBMs fit into logistics and supply chain strategy, a comparative approach was adopted in which CLBMs were compared with traditional logistics strategies wherever possible.

The comparative approach was the impetus for Essay 1's guiding research question that focused on one specific CLBM, Crowdsourced Logistics (CSL). That research question was, *"How does a crowdsourced fleet [of last mile delivery drivers] compare to a traditional dedicated courier fleet in terms of logistics effectiveness under dynamic task environment conditions?"* A stochastic discrete event simulation grounded in empirical parameters was developed to compare the two fleet types in terms of logistics effectiveness in conducting last mile deliveries with time windows. The results of Essay 1 suggested how CSL can be used in last mile deliveries and what it means for logistics and supply chain strategy. Because CSL relies on a fleet of amateur drivers with autonomy of their own work schedules, a crowdsourced fleet's delivery capacity has a large amount of uncertainty associated with it since drivers may or may not be available on demand. As a result, the logistics effectiveness is lower for a crowdsourced fleet than it is for a dedicated delivery fleet. However, an exception to this trend was found. In cases where demand for same day deliveries surged beyond the capacity of a dedicated fleet, crowdsourcing resulted in more total deliveries being made, albeit with lower on-time delivery rates. This finding implies that CSL is a means of quickly increasing capacity and responsiveness, or agility in the last mile of the supply chain. The finding also implies that while a purely crowdsourced fleet of delivery drivers may have a negative effect on logistics customer service, there is potentially value to be created in developing a hybrid delivery fleet comprised of both crowdsourced and dedicated drivers.

Essay 1 also highlighted an important consideration to using CSL, and CLBMs more generally, not prevalent in traditional B2B or B2C relationships. The logistics effectiveness of a crowdsourced delivery fleet is highly impacted by the acceptance rate at which drivers decide to make deliveries. A positive curvilinear relationship was found showing that acceptance rates below 75% result in smaller pools of available drivers and thus significantly lower on-time delivery performance. This implies that adopting a crowdsourced logistics strategy for last mile operations requires dynamic supply management strategies that monitor acceptance rates and fleet size on a continuous basis to ensure high quality logistics customer service.

Essay 1 also revealed the potential of CLBMs not only for the last mile of the supply chain but upstream tiers as well. So, Essay 2 was developed as an inductive, empirical research effort to uncover more general logistics and supply chain strategy implications of the broader class of CLBMs. Those strategy implications for the value co-creation process would be identified by exploring the following research question: "*Why and how do CLBMs impact omnichannel logistics and supply chain strategy?"* A multimethod study was developed that paired a content analysis of web-based archival data with expert Delphi panels consisting of experienced logistics managers and executives. The studies were developed using a design science paradigm to contribute generic designs of CLBMs that can be integrated into logistics and supply chain strategy.

Two main findings emerged from Essay 2. First, integrating CLBMs into omnichannel supply chains alters value cocreation processes through the idea of "competitive collaboration." Competitive collaboration is a concept synthesized from previous literature, where a firm's collaboration with the crowd to co-create value for end customers is hindered or facilitated by the firm's ability to compete with crowd members' alternative interests. This means that the act of sourcing logistics capabilities from the crowd challenges traditional thinking in that the would-be logistics service provider is not necessarily available to enter into a long-term contract. Thus, to implement CLBMs into logistics and supply chain strategy, firms have to develop novel supply management capabilities to ensure sufficient reliability of the crowdsourced asset.

Second, eight different CLBMs were identified in the study as being viable supplements to logistics and supply chain strategy. A generic typology was developed that can be used to classify the different CLBMs based on the tier of the supply chain in which they're applicable, the movement direction of the package for those CLBMs used in the last mile, and the type of relationship that governs the CLBM. A design for the integration of CLBMs into an omnichannel logistics strategy in terms of contexts and design considerations was also provided. Through the expert Delphi process, consensus of expert opinion was achieved on what contexts or environmental conditions would likely affect the success of CLBMs in practice in terms of Cost, Quality, Innovation, Flexibility, and Delivery. The expert panels identified geographical regions, delivery urgency, and product characteristics as the most important contextual factors to consider when trying to adopt CLBMs since some CLBMs are more likely to be successful in some contexts but not in others.

Essay 3 built on CSL's logistics performance outcome from Essay 1 and the contextual factors from Essay 2 to begin exploring the financial performance implications of crowdsourcing last mile delivery. **A**n empirically grounded simulation optimization model was developed to continue the overall comparative approach of this dissertation to examine several research questions related to the use of crowdsourced delivery in last mile logistics: *1) How do dedicated and crowdsourced fleets compare in terms of profitability when providing home delivery services? 2) What is the optimal size and mix of a hybrid dedicated-crowdsourced fleet when providing same day delivery of various product types in an omnichannel network? 3) What is the nature of the cost-service tradeoff when using a hybrid fleet comprised of both dedicated and crowdsourced drivers?* Three major findings regarding operational and financial performance of crowdsourced logistics for last mile delivery were made.

First, when charging customers for home delivery, CSL is generally more profitable than dedicated logistics for home delivery. However, the added cost benefit comes at lower service quality, since there is more uncertainty in the reliability of what is essentially a fleet of amateur drivers as found in Essay 1. Evidence was found suggesting that shipping functional products directly from storefronts can be more profitable when using a crowdsourced delivery fleet than with a dedicated one.

Second, a hybrid delivery fleet for same day delivery comprised of both dedicated and crowdsourced drivers provides interesting results. The size and ration of dedicated-to-crowdsourced drivers in a hybrid fleet are impacted by not only fleet costs, but product types (as implied in Essay 2), and logistics strategy in terms of pursuing a minimize cost or maximize responsiveness strategy. To minimize delivery costs, fleet sizes should be as small as possible because fewer delivery costs are incurred with fewer drivers, but to maximize responsiveness, larger fleet sizes are needed. The fleet mix ratios vary as well depending on logistics strategy. When minimizing cost, dedicated-heavy hybrid fleets are favorable for last mile delivery, especially when dedicated delivery costs per mile are low. This isn't necessarily the case with crowdsourced drivers though. When crowdsourced driver remuneration is low, the driver acceptance rate remains low as well, thus, the ability to perform same day deliveries is diminished.

Lastly, the logistics cost-service tradeoff must be balanced when using a hybrid fleet of delivery drivers. Generally, under a minimize cost strategy, it is more expensive and more difficult to provide same day delivery services since there would be lower delivery capacity in a hybrid fleet that is sized to minimize cost. However, this isn't necessarily the same result under a maximize responsiveness strategy. It could be anticipated that as responsiveness increases, so too would delivery costs, but Essay 3 showed an opposite trend: as responsiveness increases, delivery cost with a hybrid fleet would decrease when providing same day delivery of functional products from a customer's nearest retail storefronts. This finding also aligns with findings from Essay 1 suggesting that crowdsourced logistics may be best suited for delivering low cost products with predictable demand.

To sum up the results of the dissertation, CLBMs, and CSL in particular, present attractive opportunities for innovation in logistics and supply chain management strategy. CLBMs can be a means of increasing supply chain responsiveness and agility. In the case of CSL, the prominence of sharing economy workers in urban areas means that there is potentially a surplus of delivery agents for retailers to tap into for last mile deliveries. There are also fewer fixed costs and capital investment associated with CLBMs since firms crowdsource independent contractors or share assets with other firms. CLBMs and CSL introduce new risks though and should be mitigated accordingly.

VITA

Vince Castillo is a PhD Candidate in Supply Chain Management at the University of Tennessee, Knoxville. He has recently accepted a faculty position at The Ohio State University as an Assistant Professor of Logistics. His research interests include omnichannel distribution, urban delivery, sharing economy, and sustainability topics within the logistics and supply chain management domain. Vince's research has been published in the *Journal of Business Logistics* and has been presented at the Council of Supply Chain Management, Decision Sciences Institute, and Western Decision Sciences Institute annual conferences. Vince is also a member of the Academy of Management and The PhD Project.

Prior to enrolling at UT in 2014, he earned an MBA at the University of San Diego with emphasis on Supply Chain Management and Finance. He also holds a Bachelor of Science degree in Civil Engineering from the Colorado School of Mines (2006). Prior to beginning his PhD, Vince served nine years as an infantry officer in the California Army National Guard including one tour of duty in Iraq. His corporate experience spans logistics, procurement, manufacturing, customer and supplier relationship management, and engineering in the utilities, construction, and health care industries.