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Consumer sensitivity to delivery lead time: a furniture retail case

Gaetano Marino
Department of Management and Production Engineering, Politecnico di Torino, Turin, Italy
Giulio Zotteri
Interuniversity Department of Regional and Urban Studies and Planning, Politecnico di Torino, Turin, Italy, and
Francesca Montagna
Department of Management and Production Engineering, Politecnico di Torino, Turin, Italy

Abstract

Purpose – Short delivery time is a feature that can influence consumers' purchasing decisions and that retailers compete over fiercely. Accordingly, evaluating the effect of delivery time on demand and identifying marketing-mix variables that alter this relationship may influence retailers' strategies and impact supply chain (SC) performance. The paper aims to discuss these issues.
Design/methodology/approach – This study was performed in collaboration with the largest furniture retailer in Italy, which provided its sales and inventory data for 19,000 units sold over a six-month period in 32 stores throughout Italy. Data were analysed using logistic regression with fixed effects.
Findings – The value of delivery time for consumers, even in an industry generally characterised by long delivery lead times, is surprisingly high. The evidence reveals that when the delivery time changes from two days to seven days, demand is reduced by 37.5 per cent, although variables related to location and the marketing mix moderate this relationship.
Practical implications – Retailers can use the findings presented herein to drive their inventory and facility planning decisions and support investments in SC integration.
Originality/value – Supply chain management (SCM) studies consider the value of delivery time anecdotally and have neglected empirical estimations of the magnitude of the effects of delivery time on consumer demand. Further, SCM studies have not explored the factors moderating this relationship, although intertemporal choice and service management studies have demonstrated the existence of such factors.

Keywords Operations management, Logit model, Inventory management, Consumer intertemporal choice, Delivery lead time, Furniture retail

Paper type Research paper

Introduction

Delivery time is a key factor when customers make purchasing decisions (*MH&L*, 2016) and therefore its reduction offers retailers the potential to increase their competitiveness (Mak, 2018). Online retailers compete fiercely by offering shorter delivery times (Lim and Dubinsky, 2004; *MH&L*, 2016). In the early years of online retail, firms in this sector struggled to compete with the traditional retail firms (Brynjolfsson *et al.*, 2009). However, online retailers identified quick delivery as a relevant factor in competition (Brynjolfsson *et al.*, 2009). This strategy has been so successful that it has dramatically altered consumers' expectations regarding acceptable delivery times (Kumar *et al.*, 2000). Currently, roles appear to have been definitively reversed such that online retailers drive expectations about delivery, and traditional retailers must adapt to compete (Baskin, 2017). To date, many brick-and-mortar retailers have still not confronted this issue; they continue to operate exclusively based on make-to-stock (MTS) policies and physical stores. Nevertheless, operating across multiple channels is becoming a necessary condition for retailers to remain competitive (Brynjolfsson *et al.*, 2009). Consequently, traditional retailers will have to address the issue of delivery time (Ishfaq *et al.*, 2016),

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and online retailers will have to consider the benefits of offering physical locations such as stores and showrooms (Brynjolfsson *et al.*, 2009).

Academics and practitioners from different disciplines recognise that waiting times affect consumer satisfaction and preferences (e.g. Zauberman and Urminsky, 2016; Xing *et al.*, 2010; Rao *et al.*, 2011; Murfield *et al.*, 2017). However, the literature has neglected to empirically quantify these effects on demand for goods; existing evidence is still based on anecdotal evidence rather than quantitative analysis (Fisher *et al.*, 2016). Moreover, even though service management studies investigated this issue by building a link with the intertemporal choice literature and exploring factors that alter consumer sensitivity to time (Bielen and Demoulin, 2007), supply chain management (SCM) studies have overlooked these factors and their implications for physical distribution of goods (Murfield *et al.*, 2017).

To that end, by collaborating with a major furniture retailer in Italy, the present study empirically estimates the effect of delivery lead time (DLT) on retail demand for furniture as well as the moderating effects of variables related to physical stores (e.g. location and in-store display assortment) and the marketing mix (e.g. price).

Furniture was selected for the case study because it matches the criteria for high-involvement purchases. For these purchases, in fact, consumers are motivated to process a large amount of information before making a purchase decision, which thereby affects their expectations for product and service performance (Smith and Bristor, 1994).

The retailer under investigation, hereafter referred to as "the retailer" or "the Italian retailer", provided data for a balanced panel data set covering 1.2-million demand observations for this study. These data were analysed using logistic regression with fixed effects to estimate whether a single-day variation in delivery time significantly affects demand.

The present study contributes to the SCM literature by providing an empirical estimation of the magnitude of the effect of variations in the promised delivery time on retail demand, demonstrating that consumers are highly sensitive to this attribute when buying furniture, a product category usually characterised by long delivery times. Moreover, the study shows that several variables moderate the effect of DLT on demand.

The evidence provided may have significant consequences for supply chain (SC) configuration, particularly if one considers issues such as inventory strategies, selection of suppliers, and level of integration with such suppliers, among others. The findings suggest that contributions from other domains, such as consumer behaviour related to intertemporal choices and purchase involvement, can provide meaningful insights for SCM.

The paper is structured as follows. First, the literature review explores the link between consumer intertemporal choice, service management, and SCM fields in terms of the relationship between consumer behaviour, waiting times, and demand. Consistent with the reviewed literature, the "Problem formulation" section develops the hypotheses to be tested. Next, the "Case under investigation" section introduces the furniture retailing industry, with a focus on Italy, and presents the case company. Following that, the methodology is described, and findings from the empirical data are presented. The final sections include a discussion, in which the findings are compared to those in the literature, as well as a summary of implications for academia and business practice.

Literature review

Consumer intertemporal choices

Consumer intertemporal choices are decisions that involve an evaluation of trade-offs among costs and benefits, which may occur at different times (Frederick *et al.*, 2002). These choices play a significant role in fields such as psychology, economics, business, and public policy, among others (Zauberman and Urminsky, 2016).

This stream of literature generally recognises consumers' preference for shorter rather than longer delays, because time is perceived as a cost (Leclerc *et al.*, 1995). Hence, consumers usually prefer delayed outcomes only if a longer waiting time results in a higher future value.

Early models of intertemporal choice assumed that the value of time or its discounting factors were constant and positive (Samuelson, 1937). However, recent studies have demonstrated that multiple anomalies can infringe on this principle (Zauberman and Urminsky, 2016). Particularly, the time-discounting factor decreases as the length of wait time increases (Thaler, 1981). Additionally, consumers have a higher sensitivity to time for lower-value outcomes compared to higher-value outcomes (Thaler, 1981), which means that consumers appear to be more time sensitive about low-priced products.

Other effects can influence the time-discounting factor and consumers' willingness to wait (Loewenstein and Thaler, 1989). These effects concern framing intertemporal choices (Loewenstein and Thaler, 1989; Read *et al.*, 2013), individuals' status such as gains, losses, and previous experiences (Thaler, 1981; Antonides *et al.*, 2002), and contextual factors such as the social context and the environment (Loewenstein and Thaler, 1989; Pyone and Isen, 2011). Under certain conditions, consumers might prefer to delay an event's occurrence. For instance, at times, waiting can increase the expectation of pleasure from the future event (Loewenstein, 1987), or time perception can be altered by contextual factors (Antonides *et al.*, 2002). According to the literature, consumers generally prefer outcomes with shorter waiting times. However, other factors can moderate or even reverse this preference.

Value of time in service management

Waiting time has many relevant implications in the service industry because it mirrors the match between supply and demand (Mittal, 2016). Waiting time consists of time spent in queue, such as the time spent in queue at the post office, and production time, represented by the time necessary for the mailing service to be complete. Delays in providing services, particularly when demand fluctuates, can reflect efficiency issues. One can consider how the length of the queues might fluctuate at a post office around peak times. Consequently, waiting time is considered a determinant of service quality (Parasuraman *et al.*, 1985). This consideration explains why methods for reducing waiting times and perceptions of waiting times have long been explored by service management studies. A portion of this literature specifically investigated the relationship between perceived and actual wait times and their acceptance, focussing on the antecedents and consequences of wait times on consumer behaviour. These contributions demonstrated that shorter waiting time in queues, customer satisfaction, and loyalty are strongly correlated with one another (Bielen and Demoulin, 2007; van Riel *et al.*, 2012). In fact, waiting in line is not the only factor that generates negative mental states for consumers, thereby affecting their overall service evaluation (McGuire *et al.*, 2010; van Riel *et al.*, 2012; Fullerton and Taylor, 2015). Wait time expectations can also be influenced by cues from the environment, such as crowds and the number of salespeople available in the store, which can also impact consumers' decisions to patronise establishments (Grewal *et al.*, 2003; Baker *et al.*, 2002). Definitively, Allon *et al.* (2011) quantitatively confirmed the relationship between wait time and demand. The authors' analysis of fast-food industry data revealed that a reduction in the average waiting time to access chain restaurants, like shortening queues, led to an increase in their market shares (Allon *et al.*, 2011).

Oftentimes, it is not possible to reduce waiting times and delays through more effective service operations management. In these cases, it is critical to alter consumers' perceptions of time and, thereby, their willingness to wait (Fullerton and Taylor, 2015). Accordingly, factors that influence consumers' perceptions of time have been examined in other service operations management literature (Nie, 2000). In particular, authors have identified the waiting environment, including layout, waiting area attractiveness, interaction with personnel (Bielen and Demoulin, 2007; van Riel *et al.*, 2012), value of the transaction (van Riel *et al.*, 2012), and activities to fill the waiting time (Bielen and Demoulin, 2007; McGuire *et al.*, 2010) as factors that can reduce consumers' levels of dissatisfaction associated with waiting times in queues.

In short, although service management studies have already estimated the value of waiting time reductions in service encounters and the moderating effects of contextual variables on consumers' perceptions of time, they have only focussed on queues for accessing services and neglected to examine the distribution of physical goods.

Value of time in SCM

The SCM literature addresses time issues as well. The requirement to match demand and supply is clearly also focal in this domain (Cachon and Terwiesch, 2011), but differently to service management, waiting time here represents the time a customer waits to receive the purchased product. DLT has been studied since the early 1990s in a significant portion of SCM literature. Many studies explored strategies to define appropriate DLT, either for increasing production efficiency (e.g. Weng, 1999; Wikner and Rudberg, 2005) or achieving target service levels (Spearman and Zhang, 1999). Some contributions focussed on solutions to shorten DLTs and reduce inconvenience for customers (Boon-itt and Yew Wong, 2011; Goebel *et al.*, 2012), whereas theoretical models investigated the advantages of reducing DLT (Tersine and Hummingbird, 1995). Some authors specifically assumed customer sensitivity to DLT (So and Song, 1998; de Treville *et al.*, 2014), whereas others (Li and Lee, 1994; So, 2000) demonstrated, although analytically, the benefits of shortening delivery times in regard to demand.

These contributions recognise delivery time as relevant, but they and SCM literature provide only anecdotal evidence of the impact of delivery time. Surprisingly, empirical estimations of the value of DLT reductions for consumer demand, meaning the measurement of the magnitude of this effect, have been neglected (Randall *et al.*, 2011). Also, the SCM literature has not coherently addressed the factors that can potentially moderate this relationship.

Problem formulation

The aim of this study is therefore to estimate the magnitude of the effect of variations in promised delivery time on retail demand and to determine if other factors moderate this effect. As mentioned above, a context of high-involvement purchases has been selected for the investigation. Consumers tend to exert substantial effort examining external information for high-involvement purchases (Smith and Bristor, 1994; Schmidt and Spreng, 1996), including evaluating product and service attributes by comparing a large number of alternatives (Smith and Bristor, 1994).

This propensity to process information causes consumers' expectations to build regarding performance. Consumers evaluate services and products by comparing perceived and expected performance. They are satisfied if the gap between perception and expectation is narrow and dissatisfied otherwise (Parasuraman *et al.*, 1985). This evaluation typically operates *ex post*, since consumers first set their expectations, and only after testing the product they can evaluate its effective performance. Nevertheless, this process also occurs when consumers are motivated to process a significant amount of information *ex ante* (by comparing several alternatives), as in cases involving risk perceptions, financial effort, and differentiated products, such as situations when consumers are highly involved in the purchase (Smith and Bristor, 1994; Schmidt and Spreng, 1996).

Within the present research, expected performance (DLT) acts as a reference for consumer satisfaction from an *ex ante* point of view. This assumption is consistent with the literature on intertemporal choice (Yang *et al.*, 2013), where consumer sensitivity to time horizons is shown to have similarities with consumer satisfaction about waiting times (Thaler, 1981; Loewenstein and Thaler, 1989). This represents a primary element of the originality of this paper.

Hypotheses

The literature shows that consumers prefer shorter waiting times. Accordingly, this paper establishes the following hypothesis:

H1. An increase in the promised DLT decreases consumer demand by a specific amount.

The literature on both consumer intertemporal choice and service management revealed a positive relationship between the value of an outcome and consumers' willingness to wait (Thaler, 1981; Loewenstein and Thaler, 1989; Davis and Heineke, 1994; van Riel *et al.*, 2012). In fact, intertemporal choices can be considered a problem of self-control because waiting for a reward requires effort independent of the size of the reward itself (Thaler, 1981). Therefore, consumers account for a certain fixed cost independent of the reward. Specifically, the higher the value of the future outcome and the more the consumer is involved in the decision, the lower the perceived weight of the expended effort. Accordingly, consumers are more willing to wait for a good or a service if it is perceived to be of high value because in this case, they accept that some of the costs are represented by the wait time (Davis and Heineke, 1994). Nevertheless, delivery services could represent an exception if timeliness constitutes a focal performance through which quality is evaluated (Murfield *et al.*, 2017).

Therefore, considering a situation with a high-involvement purchase, the paper proposes the following hypothesis:

H2. A product's price influences customers' sensitivity to DLT. The more expensive the product, the more customers are willing to wait for its arrival.

Thus, in high-involvement circumstances, consumers are more likely to search for external sources of information by inspecting and comparing alternatives across and within retail outlets, which can affect their intention to patronise a store or purchase a certain product.

Yang *et al.* (2013) suggested that consumers' sensitivity to DLTs might be influenced by the availability of multiple alternative retailers. Indeed, in an area with several retailers, consumers can choose among several options (Schmidt and Spreng, 1996) and easily collect information about DLTs offered by multiple retailers because of lower search costs. Finally, consumers can easily switch from a retailer with longer lead times to a retailer with shorter lead times (Kumar *et al.*, 2000; Yang *et al.*, 2013). For high-involvement purchases such as furniture, consumers are willing to invest a relatively substantial amount of time in the purchase. Thus, we expect them to be able and willing to collect information about DLTs and use this information to make a selection among retailers available in the area (Smith and Bristor, 1994; Schmidt and Spreng, 1996):

H3. A reduction in the physical distance between a retailer's and a competitor's store locations increases consumers' sensitivity to DLT for high-involvement purchases.

The literature states that consumers associate a positive outcome with waiting when they can imagine the pleasure they will derive from it in the future due to their previous experiences or information they processed (Liberman and Trope, 1998). In fact, savouring a positive outcome adds value to a delayed event, thereby increasing consumers' willingness to wait (Loewenstein and Thaler, 1989). When consumers devote high cognitive effort to processing information, giving them information increases their ability to anticipate the pleasure associated with the product (Celsi and Olson, 1988). Consequently, retailers can allow consumers to experience products by displaying them in the store. Product display has previously been demonstrated to have a significant effect on demand (Eroglu *et al.*, 2011); thus, it might increase customers' willingness to wait for high-involvement purchases. Accordingly, this study tested the following hypothesis:

H4. In high-involvement purchases, if customers can experience the product in a store, they will be more willing to wait for the product's delivery.

Figure 1 outlines these hypotheses and attempts to present the conceptual model. The arrows represent the effects of one variable on another, e.g. an increase in DLT has a negative effect (−) on demand. In contrast, the dotted lines represent the possible moderator effects, e.g. an increase in the distance from competitors, increases (+) consumers' willingness to wait for products.

Case under investigation

Context

The present paper investigates the discussed phenomena in the furniture industry using data provided by the largest furniture retailer in Italy.

Furniture is a complex product category that is generally characterised by long DLTs (Vickery *et al.*, 1995) and in which customers tend to plan their purchases carefully. Although these two elements have traditionally been assumed to reduce the relevance of DLT, the increase in competition and transformations within the industry, such as innovative and online retailers (Baskin and Stevens, 2017), have potentially changed consumers' expectations regarding DLT (Kumar *et al.*, 2000).

Furniture retailers usually display their merchandise in showrooms and offer home delivery services. This SC configuration places furniture retailers somewhere between traditional and online retailers (Xing *et al.*, 2010). Consequently, the investigation of a furniture retail case may provide insights for both traditional and online retailers.

Moreover, the furniture industry, in general, and specifically in Italy has experienced dramatic changes over the last two decades (*La Repubblica*, 2017). First, innovative retailers have changed market rules by providing appealing products at lower prices and shorter delivery times. Second, online retailing has developed and become increasingly present in the arena of furniture retail, among other sectors (Baskin and Stevens, 2017).

The Italian furniture retail market is worth approximately €13billion (*La Repubblica*, 2017) and is characterised by many small independent firms and a small group of large companies, which control a large share of the market. Two of the larger companies compete for market leadership, whereas the others are not only much smaller but also have significantly different business models. Despite the large number of firms in the industry, most do not operate with stores of comparable size to those of the retailer under investigation in this study; more significantly, they do not offer the same delivery time performance, with the exception of the retailer's primary competitor. In fact, because of high inventory costs in the sector, traditional furniture retailers usually operate based on a make-to-order (MTO) inventory policy, which considerably increases their delivery time performance (Vickery *et al.*, 1995). Nevertheless, sales performance allows them to afford the associated costs, so the two market leaders can offer large assortments of MTS products whose DLTs are significantly less than those of MTO products. Accordingly, the present

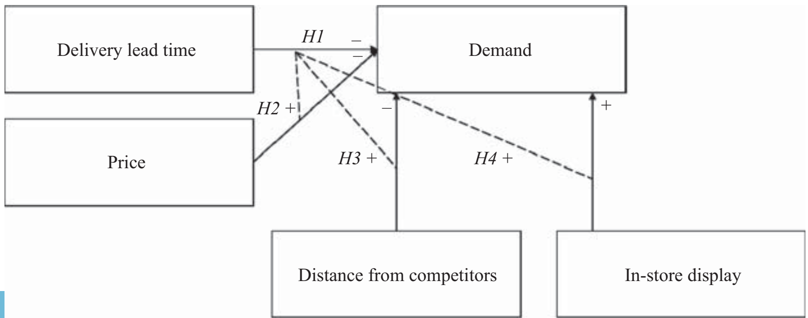

Figure 1.
Conceptual model

study only considers the chosen Italian retailer and its primary competitor as the primary competitors for the definition of a delivery time benchmark.

Within the last six years, the Italian retailer has heavily invested in warehouses to increase its number of MTS products and thereby reduce the delivery time offered to customers. This strategy has been extremely successful for the retailer, which increased its revenues at a two-digit yearly rate during this period, reaching €1billion in 2016. Hence, analysis of this successful case can offer meaningful insights not only for companies that operate in this sector but also for retailers implementing home delivery systems. Also, the findings have the potential to influence inventory management strategies, the design of supply networks, and overall operational and marketing strategies.

Case company

The retailer sells household furniture through company-owned distribution channels, which include 32 physical stores located throughout Italy, an online store and catalogues. The stores are large showrooms that range in size from 2,800 to 5,000 m^2, in which products are displayed; each store has a warehouse located nearby that handles orders collected from all channels.

The retailer offers a selection of both MTS and MTO products. MTS products are fast moving and standard products, whereas MTO products are slow moving and/or customised. For both types of products, salespeople quote an estimated DLT to potential customers after consulting the company enterprise resource planning system, which is constantly updated based on current store and warehouse information. With MTS products, the DLT quotation is based on current product availability and scheduled supplier deliveries to the warehouse. With MTO products, the DLT quotation depends upon suppliers' lead times and delivery frequency. For MTS products, the retailer offers a guaranteed two-day delivery time. When the two-day delivery promise cannot be fulfilled, such as when there is no available stock, and the DLT will thus exceed two days, the retailer offers a 10 per cent discount on the products' price.

Once the customer has gathered the necessary information about a specific product of interest, he or she can decide whether to proceed with the purchase. At this point, two alternatives are possible: the product can be delivered to the customer's home, or the customer can collect it directly from the warehouse on the promised date.

Data

The hypotheses are tested based on sales and inventory data on a single product category to avoid differences in consumer purchasing behaviour driven by differences across product categories. Specifically, couches and armchairs were identified as most adequate for this study.

Couches and armchairs were selected for a variety of reasons. First, since the retailer provides couches that are both MTS and MTO, they have high delivery time variability, which should make it easier to detect any effects on demand. Additionally, their standard sizes make them easier to receive at home, which could increase consumers' sensitivity to time. Moreover, they have a relatively high price and wide price variability, which should help identify the interaction between this variable and delivery time. Finally, couches and armchairs have a low purchasing frequency, high product differentiation, and a high level of sensory attributes, which increase consumers' desire to compare and inspect alternatives. Given these factors, it seemed reasonable to consider this case a high-involvement purchase situation. This product category choice should also increase the relevance of store location and product display as a way to compare alternatives within and between stores.

The Italian retailer provided sales and inventory information on all types of couches for all 32 of its stores over a six-month period between 2 January and 10 June 2014 of the same year. These data include daily information about transactions, product attributes (e.g. product characteristics and prices) and inventory data (e.g. supplier lead times and product availability in stores and warehouses) for each product, in each store, and on each day throughout the examined period. Hence, it was possible to build a unique database that covers operational and other contextual variables, such as distance from the closest competitor's store.

In the period considered, the retailer sold approximately 80,000 units and armchairs from a total offering of 2,800 different products; 50.3 per cent of the sales were MTS items available in stock. In these cases, short delivery times were guaranteed.

Table I describes the variables included in the data set. *DLT* represents the best delivery time the retailer could offer for a given product in a given store on a given day. Ideally, *DLT* is set to two days for in-stock products; it is longer for products that are stocked-out or equal to the supplier's DLT for MTO products. The *Product Display* variable measures the percentage of days in the month during which the product, in at least one of its colour variations, was displayed in a store. This metric was attributed to every day in the month since it was not possible to capture it on a daily level. This variable is not correlated with the product inventory policy; products are displayed in the stores, whereas units to be delivered to customers are held in the warehouses. Therefore, this variable can be equal to 0 for MTS products and 1 for MTO products. Furthermore, a series of categorical variables is used to identify the *Product*, *Store*, *Day* of the week, and *Month* of the year. The *Product Typology* variable expresses whether the product is a sofa bed or a simple sofa and its number of seats (e.g. three-seat sofa or two-seat sofa bed). The $Quantity_{ijt}$ variable represents the number of units of Product i sold in Store j on Day t. Moreover, the *Price* variable denotes the product sales price at a given store on a given day. Finally, the data set includes the *Promotion* variable, which is a binary variable that indicates whether Product i was part of a promotion in Store j on Day t.

A data panel was built based on the information on the sales and inventories of 337 products sold within the investigation period. The products included in the sample were randomly selected from those the retailer offers, and the sample size was determined according to the method proposed by Krejcie and Morgan (1970) to be representative of the entire population for each characteristic.

Name	Description	Domain and collection
Delivery Lead $Time_{ijt}$	Number of days in which the retailer promised to deliver the product to the final customer	DLT that the retailer can perform for Product i in Store j on Day t
Product $Display_{ijt}$	Percentage of days in a month during which the product, in at least one of its colour variations, was on display in the store	"0" ("1") if a given product i was never (always) displayed in a given Store j in a given month; otherwise, the fraction of the month in which the product was displayed [0, 1]
Competitor $Distance_j$	Distance between each retailer Store j and the nearest competitor's location	Distance measured in metres ranging between 850 m and 110 km
Product i	Products included in the panel	Categorical variable for each Product i sold within the period
Product $Typology_i$	Physical characteristics of each product within the data set	Categorical variable that captures both the typology of Product i (i.e. armchair, couch or sofa bed) and its number of seats (i.e. 1, 2, or 3 seats)
$Quantity_{ijt}$	Number of units sold	Quantity of units sold of Product i in Store j on Day t
Store j	Stores within the retailer network	Categorical variable for each Store j across the retailer's network (1-32)
Day	Day of the week	Categorical variable for each day of the week (Monday-Sunday)
Month	Month of the year	Categorical variable for each month within the period (January-June)
$Promotion_{ijt}$	Dummy variable that captures whether the product is discounted	"1" if Product i is discounted (in Store j on Day t) and "0" otherwise
$Price_i$	Product selling price	The price charged for a given Product i

Table I. Description of variables in the dataset

The sample covers 19K units, or more than 20 per cent of the Italian retailer's total demand for couches and armchairs within the studied period. Specifically, the panel includes approximately 1.2M demand data points, one for each product in each store (i.e. 32 stores) on each day (i.e. 161 days) within the selected period.

Products that were included had different inventory policies; 11 were MTS; 319 were MTO, and for seven, the inventory policies changed over the period. These various policies led to DLTs that ranged between 2 and 31 days, as shown in Table II. Their prices were also heterogeneous, ranging from €150 to €1,200. Six products were subject to price promotions, and on average, approximately 31 per cent of the products were displayed in stores.

Methodology

Methodologically, econometric models were adopted. These models are usually employed for estimating the effect of policies such as assortment decisions, promotions, and price on demand and for isolating the effect of various variables on a single dependent variable (Morikawa *et al.*, 2002; Petrin and Train, 2010).

Econometricians have developed a variety of discrete choice models (for a review, see Keane and Wasi, 2013) based on the nature of the purchasing decision, including whether to buy, which brand to purchase and the number of items needed.

The case under investigation aims to model consumer choice among different options based on the assumption of utility maximisation. However, both the consumer's utility function and the option attributes are heterogeneous and cannot be fully known. Therefore, random utility models are the most adequate to perform the analyses (Manski, 1977). These models allow predictions of discrete consumer choices to be made in the context of incomplete information.

The data refer to single transactions conducted by consumers; thus, they record consumer-revealed preferences for product and service attributes. Furthermore, the data show a low success rate and a low frequency of sales with 19K units over 1.2M cases. In fact, in 99.8 per cent of the 1.2M demand data points, the retailer sold none or at most one unit of the same Product i at the same Store j on the same Day t. Considering these facts, the logit model is the most suitable of the random utility models.

Logit regression predicts the probability E[Y|X] of an event occurrence, a value of 1 of a dichotomous variable, through estimating its sensitivity (β_i) to predictors (X_i) (1). Predictors can be a mix of continuous and categorical variables, and no assumption about their distribution is required:

$$E[Y|X] = \pi(x) = \frac{e^{\beta_0 + \sum_i \beta_i X_i}}{1 + e^{\beta_0 + \sum_i \beta_i X_i}} \tag{1}$$

Name	Min.	Max.	Average	SD	Type
Delivery Lead Time$_{ijt}$	2 days	31 days	29 days	5 days	Continuous
Product Display$_{ijt}$	0%	100%	31%	46%	Continuous
Competitor Distance$_j$	850 m	108 km	32.5 km	29.6 km	Continuous
Product$_i$	–	–	–	–	Categorical
Product Typology$_i$	–	–	–	–	Categorical
Quantity$_{ijt}$	0 units	11 units	0.02 units	0.16 units	Continuous
Store$_j$	–	–	–	–	Categorical
Day	–	–	–	–	Categorical
Month	–	–	–	–	Categorical
Promotion$_{ijt}$	0	1	0.01	0.086	Binary
Price$_i$	€150	€1,200	€575	€248	Continuous

Table II.
Descriptive statistics of the panel data

In this analysis, the dependent variable, Y_{ijt}, captures whether at least one unit of a given Product i at a given Store j on a given Day t has been sold, which refers to a *Sale*. Thus, E[Y| X] can be interpreted as the probability that consumers will buy at least one unit of Product i in Store j on Day t:

$$Y_{ijt} = \begin{cases} 1 \text{ if } Quantity_{ijt} \geqslant 1 \\ 0 \text{ if } Quantity_{ijt} = 0 \end{cases} \quad (2)$$

The variables reported in Table II are used as controls or predictors. They represent the product and service attributes consumers evaluate when choosing among available options.

Building the models

Four econometric models were built to analyse sales and inventories of the products included in the panel. The four models have the same structure, which is a logit regression with null or positive sales for a Product i in a Store j on a Day t as the dependent variable. However, they differ based on the hypothesis tested, such as when independent variables are explicated, and regarding which variables are included, such as when control variables change to avoid collinearity issues.

Model 1 aims to test *H1* by assessing whether an increase in *DLT* reduces the probability of selling a given product in a given store on a given day. Thus, it considers *DLT* as an independent variable and the in-store *Product Display* and *Promotion* as covariates. Furthermore, the model includes *Product* and *Store* dummy variables to control for fixed effects. *Day* of the week and *Month* of the year variables are used to control for seasonality. The *Price* variable is omitted because of its collinearity with *Product*. The fixed effects across the products capture the *Price* variance. *H1* assumes that the *DLT* β coefficient is negative, indicating that an increase in *DLT* reduces the selling probability by a certain amount to be estimated.

Models 2-4 aim at testing *H2-H4* by examining whether price, store location, and in-store product displays, respectively, moderate the relationship between DLT and demand. These models have been built to study the interaction between *DLT* and its moderators (i.e. *Price, Competitor Distance*, and *Product Display*) through a multiplicative scheme, and the interaction variables ($DLT \times X_i$) have been inserted iteratively according to the hypothesis the model aims to validate.

Specifically, Model 2 aims to test *H2* by examining customer sensitivity to *DLT* for different price levels. Customer sensitivity emerges from the interaction between the *DLT* and *Price* variables. Hence, the model considers *DLT* × *Price* as an independent variable, and *DLT*, *Price*, *Product Display*, and *Promotion* are examined as its covariates. The model includes the *Store*, *Day* of the week, and *Month* of the year as control variables. Due to the collinearity between *Product* and *Price*, Model 2 does not consider the former variable. Nevertheless, it does consider the *Product Typology* variable since it is uncorrelated with both *Product* and *Price*.

Model 3 tests *H3* through an analysis of consumer sensitivity to *DLT* across different stores located at different distances from the nearest primary competitor's store. Like Model 2, Model 3 does not consider the *Store* variable because of collinearity. The model also includes *Product*, *Day* of the week, and *Month* of the year as control variables.

Finally, Model 4 investigates *H4* by analysing the interaction between in-store *Product Display* and *DLT*. The model considers both the location variable *Store* and the variable *Product*; therefore, to avoid collinearity, other location and product variables such as *Competitor Distance* and *Product Typology* are not included. *Day* and *Month* are considered control variables. Table III summarises all the proposed models and shows the included variables, the hypothesis to be tested, and the expected results for each model.

Table III.
Description of models

Model	Hypothesis to test	Dependent variable	Independent variables	Technical hypothesis
Model 1	*H1*	*Sale* (Equation (2))	*DLT, Product Display, Product, Store, Day, Month, Promotion*	$\beta_{DLT} < 0$
Model 2	*H2*		*DLT, Product Display, Log (Price), DLT × Log (Price), Product Typology, Store, Day, Month, Promotion*	*Interaction DLT-Log (Price) > 0*
Model 3	*H3*		*DLT, Product Display, Log (Competitor Distance), DLT × Log (Competitor Distance), Product, Day, Month, Promotion*	*Interaction DLT-Log (Competitor Distance) > 0*
Model 4	*H4*		*DLT, Product Display, DLT × Product Display, Product, Store, Day, Month, Promotion*	*Interaction DLT-Product Display > 0*

Results

Table IV shows the logistic regression coefficients, their statistical significance and the effect of the predictor variables on the odds ratios (Exp(β)). Moreover, it shows the Exp(β) confidence interval at 95%. If the confidence interval does not contain the value 1, then the variable has a significant effect on the odds ratio.

In contrast, the interaction between the variables cannot be interpreted by simply observing the signs of the β coefficients for the interaction factors ($\beta_{DLT \times Xi}$) because, unlike OLS, logit models have a non-linear nature. Thus, the β coefficients do not express the sensitivity of the dependent variable to the interaction term; however, analysis of the average marginal effects (AME) of function (1) does (Greene, 2010). This sensitivity is obtained by calculating the average of the marginal effects of *DLT* on *Y* in all observations in the sample. Accordingly, the derivative of (1) is computed with respect to *DLT* at different representative values of the interacting variable.

H1: The outputs of Model 1 are significant, and the effect of the *DLT* on the odds ratios is 90.2 per cent. Because the model is non-linear, this effect is the percentage variation of the probability of selling the item. Thus, each additional day of DLT significantly lowers the probability of selling an item. This result aligns with the previous findings that identified consumers' preferences for shorter waiting times in reference to intertemporal choices (e.g. Frederick *et al.*, 2002). It also supports the relationship between waiting time and consumer satisfaction for services regarding the physical distribution of goods (e.g. Xing *et al.*, 2010; Murfield *et al.*, 2017).

Although the evidence of the effect is clear, the significant number of dummy variables included in the models called for a broader investigation to correctly interpret the magnitude of the phenomenon. Therefore, the covariates and the control variables are set to representative values, and the selling probability is computed for different levels of *DLT*. For instance, keeping all the other factors constant to values representing an average-selling case, the results show that when the promised DLT changes from two days to seven days, the probability of selling the product decreases from 10.99 to 6.87 per cent, representing a 37.5 per cent reduction in demand. Furthermore, considering the same variable setting, when DLT changes from 2 to 31 days, the probability of selling the product decreases from 10.99 to 0.62 per cent (i.e. demand is reduced by 94.4 per cent). If all the variables are set to their top-selling values, when the promised DLT changes from two to seven days, the probability of selling the product decreases from 96.02 to 93.51 per cent, which represents a 2.6 per cent decrease. However, if the DLT changes from 2 to 31 days, the probability of selling the product decreases from 96.02 to 54.81 per cent, a decrease in demand of 42.9 per cent. In the furniture industry for MTO products; 31 days is a relatively short time span; whereas two days is the

Table IV. Logistic regression results

	Model 1		Model 2		Model 3		Model 4	
Dependent variable: Sale	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)
DLT	−0.103*** (0.002)	0.902 [0.898-0.906]	−0.426*** (0.010)	0.653 [0.640-0.666]	−0.108*** (0,003)	0.897 [0.892-0.902]	−0.191*** (0.005)	0.826 [0.818-0.834]
Product Display	0.287*** (0.058)	1.332 [1.189-1.493]	0.307*** (0.029)	1.359 [1.283-1.439]	0.413*** (0,055)	1.511 [1.357-1.683]	−0.744*** (0.069)	0.475 [0.415-0.544]
Promotion	0.529*** (0.046)	1.698 [1.552-1.857]	0.634*** (0.034)	1.885 [1.763-2.015]	0.524*** (0.045)	1.688 [1.545-1.845]	0.482*** 0.046	1.619 [1.479-1.772]
Log (Competitor Distance)					−0.145*** (0.007)	0.865 [0.852-0.878]		
Log (Price)			−1.788*** (0.034)	0.167 [0.156-0.179]				
DLT × *Log (Competitor Distance)*					0.002*** (0.000)	1.002 [1.001-1.003]		
DLT × *Price*			0.046*** (0.002)	1.047 [1.043-1.050]				
DLT × *Model Display*							0.115*** (0.005)	1.122 [1.111-1.133]
Constant	−4.616*** (0.714)	0.010 [–]	9.784*** (0.217)	17,739.227 [–]	−4.313 (0.713)	0.013 [–]	−1.963*** (0.725)	0.141 [–]
Product	Confirmed		na		Confirmed		Confirmed	
Store	Confirmed		Confirmed		na		Confirmed	
Product Typology	na		Confirmed		na		na	
Days and months	Confirmed		Confirmed		Confirmed		Confirmed	
Nagelkerke R^2	0.454		0.392		0.444		0.463	
% of correct cases predicted by the model (cut 0.5)	98.93		98.91		98.93		98.93	

Notes: The values shown in parentheses are the B standard errors, whereas the values in brackets are the lower and the upper bounds of the 95% confidence intervals of Exp(β). Significance of variable: $^{*}p < 5$ per cent; $^{**}p < 1$ per cent; $^{***}p < 0.1$ per cent retailer's typical DLT for MTS products, suggesting that the inventory investment, the effort required for supplier selection and the integration level required for Italian retailers to practice the MTS model might be worth the effort.

Further detailed analyses were performed on a few selected products to validate the results. The inventory policies for the selected products changed within the examined period, shifting the product's status from MTS to MTO or vice versa, whereas their other operational variables were not changed during the considered period (i.e. *Product Display*, *Price*, or *Promotion*). As a result, DLT performance decreased or increased depending on the change in status; thus, sales performance also decreased or increased over a range between ±30 and ±60 per cent. Since *DLT* was the only variable that changed, customers could not be aware of the change in inventory policy. These results confirm again that *DLT* influenced the probability of a sale and not vice versa.

H2: the results from Model 2 are also statistically significant, and the results for the β coefficient of the interaction term between *DLT* and *Price* are positive, although, as mentioned above, they do not indicate an absolute positive interaction, as would be seen in linear models (Greene, 2010). The AME is computed in all the observations by keeping the interacting variable (i.e. *Price*) constant to representative values (i.e. deciles), and the average is calculated. Table V shows that in Model 2, AME increases with increasing values of *Price,* which indicates that the interaction between *DLT* and *Price* is also significantly positive overall. Hence, the higher the product price, the less sensitive customers will be to DLT variations.

In fact, considering the average selling case, when the *DLT* shifts from two to seven days (from 2 to 31 days), demand decreases by 54.14 per cent (99.5 per cent) for a €150 product and by 39.9 per cent (94.85 per cent) for a €1,200 product, respectively. Thus, the results show that an increase in *DLT* shrinks demand for low-priced products slightly more significantly than for expensive products. This higher consumer propensity to wait for more expensive products not only confirms previous findings on the customers' willingness to wait (Kremer and Debo, 2015) but also extends the relationship between consumer sensitivity to time and perceived outcome value (van Riel *et al.*, 2012) to the anticipated reward from the consumer goods.

H3: the same type of approach was implemented for Model 3. In this case, the signs of the β coefficients of the interaction terms are confirmed by the difference between AMEs, as seen in Table V. Therefore, the *DLT* × *Competitor Distance* variable significantly affects demand because it is characterised by overall positive interaction effects. If the average selling case is also considered for this model, when *DLT* shifts from two to seven days (from 2 to 31 days),

		$\frac{\partial Y}{\partial DLT}$								
		Price (Model 2)		Competitor Distance (Model 3)			Product Display (Model 4)			
Decile	Value	AME	SD	Value (km)	AME	SD	Value (%)	AME	SD
10	€262	−0.00985***	(0.00044)	3.3	−0.00119***	(0.00004)	0	−0.00214***	(0.00009)
20	€340	−0.00726***	(0.00028)	7	−0.00108***	(0.00003)	0	−0.00214***	(0.00009)
30	€396	−0.00605***	(0.00022)	10.3	−0.00102***	(0.00003)	0	−0.00214***	(0.00009)
40	€485	−0.00470***	(0.00015)	15.6	−0.00097***	(0.00003)	0	−0.00214***	(0.00009)
50	€565	−0.00385***	(0.00011)	26.9	−0.00090***	(0.00002)	0	−0.00214***	(0.00009)
60	€686	−0.00296***	(0.00007)	33.3	−0.00087***	(0.00002)	0	−0.00214***	(0.00009)
70	€686	−0.00296***	(0.00007)	33.8	−0.00087***	(0.00002)	84	−0.00150***	(0.00004)
80	€857	−0.00260***	(0.00006)	63.8	−0.00080***	(0.00002)	100	−0.00140***	(0.00003)
90	€920	−0.00193***	(0.00004)	73.7	−0.00078***	(0.00002)	100	−0.00140***	(0.00003)

Notes: Significance of AME: *$p < 5$ per cent; **$p < 1$ per cent; ***$p < 0.1$ per cent

Table V.
Average marginal effects of DLT

demand is reduced by 36.8 per cent (94.7 per cent) in a store 850 metres away from the competitor's location, respectively. However, demand is reduced by 35.6 per cent (93.0 per cent) in a store 108 kilometres from the competitor's location. This finding indicates that *DLT* has a greater effect on demand in stores located closer to a competitor's location.

This evidence appears to confirm that higher information availability affects consumer behaviour in high-involvement purchases (Schmidt and Spreng, 1996) and the existence of a benchmark effect in the definition of consumer time requirements (Yang *et al.*, 2013). More specifically, the results suggest that in local markets where retailers are located nearby, consumers' preference for shorter DLTs is stronger. This finding may have more significant implications in the case of low search cost instances since low search costs like those available with online retailing make comparisons easier.

Intuitively, this finding appears to be reasonable because if potential customers know they have easy access to another store that could provide better performance, namely a shorter delivery time, they might decide to refuse to buy from a retailer with a longer *DLT* and instead purchase from a competitor.

Although these findings show the effect of a strategic interaction on time competition, they may additionally support the assumption that a retailer's location choices might also influence results (Glaeser *et al.*, 2001). In fact, both retailers tend to be located close to the same large cities, and the distance between their respective stores in these large cities is consequently shorter; however, only one of the retailers tends to be in smaller cities. Thus, the distance between their competitors' locations is greater. Therefore, the level of competition and cultural attitudes of people who live in metropolitan areas might influence consumer requirements for shorter DLTs (Glaeser *et al.*, 2001). Nevertheless, the phenomenon is illustrated clearly by the model, and the hypothesis is confirmed.

H4: finally, the *Product Display* variable also interacts with the *DLT*. As in previous cases, the relationship among the representative values confirms the hypothesis. In fact, the AME decreases with increasing *Product Display* values. Therefore, when products are available to be touched and felt in a store, the *DLT* has a lower effect on consumers' purchasing decisions because in-store displays increase the consumers' ability to anticipate the future outcome, thereby increasing their willingness to wait (Berns *et al.*, 2007; Bartels and Urminsky, 2015), as was previously recognised in the intertemporal choice literature. In fact, when DLT shifts from two to seven days (from 2 to 31 days), demand decreases by only 29.2 per cent (87.8 per cent) for a product that is displayed in-store and by 57.0 per cent (99.5 per cent) for a product that is not displayed.

Discussion and conclusion

Summary of findings

The results confirm the relevance of DLT as a driver of customer purchasing decisions by demonstrating that shortening or extending DLT significantly increases or decreases, respectively, retail demand. Contextual variables can moderate this effect, and their effects are relevant as well.

In particular, the results provide evidence of an interaction between product value and DLT by illustrating that when consumers are highly involved in purchases, they are more willing to wait for more expensive products. Also, in such circumstances, the level of competition in the local area can alter consumers' sensitivity to DLT, and consumers who buy from stores located close to competitors are more likely to react to DLT changes than are consumers who purchase from stores located further away from competitors. Finally, when consumers can touch products that are displayed in the stores, they tend to be less sensitive to changes in DLT.

The proposed models confirm the negative relationship between DLT and demand, confirmed by the robustness of the results. The sign and magnitude of the β coefficient associated with DLT are shown to be stable. Several models with different sets of variables and subsamples (i.e. different subsets of products and different subsets of stores) have been additionally tested to analyse the robustness of the results. Furthermore, numerical examples have been proposed to analyse DLT and its covariate effects by setting the variables to representative values, thereby helping the reader interpret the results and providing an idea of the magnitude of the phenomena.

These results are significant and have additionally been validated by further evidence from the Italian retailer. A series of interviews with customers revealed that one of the most frequently requested service attributes concerns the speed of delivery. The retailer's customer service department randomly contacts 10 per cent of its customers by telephone and asks them three open questions regarding their levels of satisfaction. The retailer conducts over 100,000 interviews each year, and the results show that the most-relevant attribute for customers is delivery time reliability, followed by the actual delivery time. This demonstrates customers' sensitivity to time-related issues. Furthermore, approximately two-thirds of all the items that the retailer sells, not only couches and armchairs, are delivered within two or three days of the purchase date thanks to the retailer's major investments in warehouses, inventory, and processes. These investments have led to the growth of MTS products from 30 to 53 per cent of gross sales over the past six years.

Implications for research

The referenced literature establishes the consumers' preference for shorter waiting times in several fields and contexts (Zauberman and Urminsky, 2016). The intertemporal choice literature examines the consumer preferences for anticipated outcomes as a postulate (Frederick *et al.*, 2002), while the service management literature recognises wait time in queues as a source of consumer dissatisfaction (van Riel *et al.*, 2012; Fullerton and Taylor, 2015). Finally, the SCM literature identifies delivery timeliness as a driver of the perceived quality of physical distribution services (Xing *et al.*, 2010; Rao *et al.*, 2011; Murfield *et al.*, 2017). Nevertheless, while the intertemporal choice and service management research streams have estimated the magnitude of these effects empirically (Bartels and Urminsky, 2015; Allon *et al.*, 2011) and, more relevantly, have identified moderating factors, surprisingly, SCM has not investigated such effects. Therefore, the relationship between the magnitude of the phenomenon, the moderating variables, and the consequences they can generate in managing SCs still needed to be explored.

Accordingly, this paper contributes to the literature by empirically estimating the magnitude of the effect of the promised DLT on high-involvement purchases through an *ex ante* perspective on consumer purchasing behaviour and by identifying product price, store location, and in-store product display as moderators.

Managerial implications

From a managerial perspective, the results suggest to retailers that a reduction in DLT can significantly increase demand for consumer goods, although other factors can substantially affect this relationship.

Clearly, the results are context dependent, and, in this specific case, they refer to furniture retailing, an industry that used to be characterised by long DLTs (Vickery *et al.*, 1995) and consumers who tend to plan their purchases carefully. Thus, it is assumed that consumers should be less sensitive to DLT (Loewenstein, 1987). Although these antecedents suggest that time should not be a relevant variable that affects consumers' choice of furniture, the presented results demonstrate that the magnitude of this effect can be managerially relevant. Moreover, investigating the time between in-store order placement and promised delivery, as well as analysing the interaction between variables related to physical stores (e.g. store location, in-store display, and delivery time), can provide interesting insights for retailers operating across multiple channels that offer a buy-in-store and ship-direct purchasing experience.

Specifically, the results appear to encourage improvements in time performance. Consequently, retailers could implement several actions involving their internal structures and their relationships within the SC. Single retailers might decide to invest in additional warehouse space to increase their stock and carry broader assortments in stock. Also, they could consider redesigning their processes and systems to reduce DLTs from their warehouses to consumers. More generally, the level of integration within the SC can have significant effects on time performance (Boon-itt and Yew Wong, 2011).

The results suggest a need to improve time performance in areas where competition is tough and where consumers tend to value time performance more, namely, in larger cities (Glaeser *et al.*, 2001). Accordingly, retailers could locate larger distribution facilities in these areas to avoid stock-outs and reduce shipping times. Anecdotally, Amazon's substantial investments in distribution facilities located near urban areas appear to confirm this evidence.

Alternatively, retailers might consider the moderating effect of in-store product displays to reduce consumers' sensitivity to DLT. Retailers could increase available space for showrooms in stores to let consumers experience more products and thereby moderate their delivery time desires. In fact, online retailers, which are unable to allow consumers to inspect their products, must rely on quick delivery to fill the gap between them and traditional stores.

Nevertheless, when defining their delivery strategy, retailers should consider that other factors can alter consumers' time perceptions. Among such factors, the results provide evidence that consumers are more willing to wait for higher-priced products. Consequently, retailers should focus on reducing DLTs for their less valuable but more DLT-sensitive products rather than focussing on reducing DLTs for their higher-priced products. In general, the results indicate that retailers should consider the effects of purchase involvement and the search for external information in setting consumers' expectations regarding DLT performance.

Although these results suggest good revenues for retailers and suppliers that can reduce their DLTs, it is important to bear in mind that the decision regarding whether to make such investments should include a cost estimation and specific analyses that are beyond the scope and objective of this paper.

Limitations and further investigations

This study empirically contributes to the literature by supporting the definition of strategies that include consumer behaviour theories such as intertemporal choice and purchase involvement in SCM.

However, as in any empirical research, the depth of the analysis is limited by the available data. Although the case under investigation analyses thousands of demand observations, the results are limited to a single company in a single industry within a single market. Nevertheless, the great number of consumers who shop at this retailer, more than 1.5M in 2016, reveals that a large share of the consumers in Italy, the world's eighth-largest economy, are considerably sensitive to DLT for a product category generally considered less sensitive to time performance than others.

Another issue relates to the substitution effects between products. When a product is not available in stock, customers might decide to wait for it, or they might switch to another product that they perceive as being similar. In the worst-case scenario, they choose to make their purchase from another store. Moreover, because of the vast assortment the retailer provides, a switch of product is more likely to occur, thereby definitively affecting product demand. Therefore, if an analysis of the substitution effects had been performed, it could have provided further evidence that time performance affects consumers' purchasing decisions.

Consequently, despite the authors' belief that these results can be applied outside the retail furniture industry in Italy, the outcomes and limitations suggest several areas for future research based on the DLT issue and, more generally, consumer behaviour implications for SCM. For instance, extending the analysis to different product categories and markets could definitively determine whether the consumers' sensitivity about DLT depends upon the product category, the industry, or the Italian market. In contrast, the relationship between DLT and product displays suggests that the purchasing experience affects consumers' time requirements; thus, the chosen retail channel might influence their sensitivity to time performance. Therefore, comparing the relevance of DLT for customers who shop among various retail channels would be beneficial.

Finally, studies could investigate the point at which companies should stop investing in shorter lead times, such as whether decreasing delivery time from two days to two hours still offers pay-offs in terms of increased demand. Also, the long-term effects of actual DLTs and the reliability of the promised delivery dates should be further investigated. In fact, the reputation of a company in regard to its adherence to the promised delivery performance may influence consumer choice even more significantly.

More generally, as this study has demonstrated for delivery time, the exploration of consumer characteristics and behaviours has significant implications for both single retailers and SCs. Therefore, further investigation is warranted.

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Corresponding author
Gaetano Marino can be contacted at: gaetano_marino@polito.it