Received: 13 October 2020 | Revised: 18 March 2022 | Accepted: 27 May 2022

DOI: 10.1002/joom.1204

RESEARCH ARTICLE

WILEY

Estimating impacts of logistics processes on online customer ratings: Consequences of providing technology-enabled order tracking data to customers

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Handling Editors: Gregory Heim and Xiaosong (David) Peng

Abstract

Recent advances in logistics tracking technologies have enabled e-commerce firms to both accurately track the shipments and obtain accurate estimates of delivery times. With customers constantly tracking the status of their orders, the effects of logistics processes on customers' evaluation of their online shopping experience are relatively unknown as academic literature provides little guidance. Drawing upon the expectation-disconfirmation theory and attribution theory, and using a unique dataset assembled in collaboration with an e-commerce firm, we empirically investigate the effects of order processing and delivery times on online customer ratings. We also estimate the impact of positive deviation (i.e., early delivery) and negative deviation (i.e., late delivery) from the promised delivery date on online customer ratings and whether the impact of delivery status (early or late) depends on order cost and freight cost. Our empirical findings demonstrate that longer order processing and delivery times are associated with lower ratings. Our results also highlight that the late delivery of an order is negatively associated with ratings and that the order cost amplifies this effect. Furthermore, freight cost reduces both the negative effect of late delivery and the positive effect of early delivery on online ratings. Our results also indicate that there exist curvilinear relationships between online ratings and the number of days an online order is late or early. Specifically, the negative effect of a late delivery follows a convex-shape curve such that its impact decreases as the number of days an online order is late increases. Likewise, the positive effect of an early delivery increases at a decreasing rate as the number of days an online order is early increases. Our supplementary analyses further account for potential endogeneity issues and corroborate our main results with additional empirical evidence obtained through alternative model specifications and estimation strategies. We present important theoretical implications and managerial takeaways from our findings.

KEYWORDS

e-commerce firms, logistics tracking, online customer ratings, order processing times, shipment delays

1 | INTRODUCTION

With the advent of online shopping platforms and omnichannel retailing, the current shopping journey for customers involves multiple channels such as online, catalog, and brick and mortar (Akturk et al., 2018). Even when customers make a purchase in a physical store, the search process for most consumers starts with the online channel where they gather information about different products (Bell et al., 2014; Verhoef et al., 2015). As such, online customer ratings have become a popular asset for online and offline shoppers to collect information about product quality (Kwark et al., 2014; Zhu & Zhang, 2010) and are seen as a measure of customer satisfaction of an online order (Engler et al., 2015).

Previous research demonstrates that online ratings in e-commerce marketplaces represent one of the most popular tools in influencing consumers' purchase decisions (Jiang & Guo, 2015). Similarly, anecdotal evidence and several industry reports highlight the importance of online ratings on consumers' decision to purchase the product. For example, a survey by Podium reports that 93% of respondents indicate that online customer ratings impact their purchase decisions (Podium, 2017). Evidently, it is important for firms to ensure that customers' expectations are fully met so that they can receive positive ratings on e-commerce platforms.

Given that online ratings significantly affect customers' purchase behaviors, firms have taken steps to improve the overall shopping experience. A critical component of online shopping is timely delivery of orders (Heim & Field, 2007; Wan et al., 2016). As such, retailers have started to invest in emerging Industry 4.0 technologies to improve the efficiency in processing and delivering online orders. These technologies include internet of things (IoT), artificial intelligence, and cloud computing, among others. For example, e-commerce firms are utilizing IoT networks along with bar coding and radio tags to accurately track the location of packages (Yen, 2021). Furthermore, retailers are leveraging cloud computing technologies to handle large volumes of information obtained from these sensor networks and employing artificial intelligence to accurately estimate the delivery times.

These advanced technologies also enable retailers to share detailed, up-to-date information regarding their order fulfillment processes with customers. Recent anecdotal evidence indeed suggests that customers also expect retailers to provide detailed information about the current status of their order (Magloff, 2020). For example, Lopienski (2019) reports that over 97% of customers expect the ability to monitor the status of their online orders during the entire shipping process. Likewise, a survey by OSM Worldwide (2016) reveals that 40% of customers track the status of their online orders at least once every day, while 55% of the customers expect status updates to be accurate within a few hours of time period. Evidently, the impact of these technologies reaches beyond retailers' internal operations as they may influence how customers evaluate their shopping experience.

With online customers constantly tracking the shipping status of their online purchases, it is important for firms to understand how deviations in logistics (or order fulfillment) processes affect online ratings. Order delivery performance has been widely studied in the operations and supply chain management literature as customers expect to receive the correct product in the right quantity at the promised time (Fisher, 1997). Previous studies have shown that on-time delivery is positively associated with return on assets (Corbett & Claridge, 2002), return on sales (Morash et al., 1996), and customer satisfaction (Griffis et al., 2012; Rosenzweig et al., 2003). Whereas prior research generally considers order fulfillment performance as the final outcome of the order fulfillment process (i.e., the actual time of delivery), research on examining whether and how the processing times associated with fulfilling online orders (i.e., the order fulfillment process before actual delivery) impact customer satisfaction is limited. Our research seeks to fill this gap in the literature by empirically examining the effects of order fulfillment times before the actual delivery (reflected by order processing time and delivery time) in addition to the outcome of delivery on customers' perception of an online order.

Furthermore, prior studies examine the impact of order fulfillment processes by focusing mostly on developed economies while the extant marketing research has shown varying expectations of customers in developed and developing economies (Morgeson et al., 2015). In addition, developing economies have witnessed an exponential growth in e-commerce sales during recent years (Vena, 2020). Yet, to the best of our knowledge, research on understanding customers' evaluation of order fulfillment processes in developing economies is limited. Thus, deviating from the earlier studies, our study uses a data set from an e-commerce firm (online retailer) in South America to systematically document the effects of logistics processes on online customer ratings in a rapidly growing developing economy.

1.1 | Motivation and research questions

Online shopping platforms are increasingly adopting logistics tracking technologies so that they can share up-to-date information regarding their order fulfillment process with customers. In an order fulfillment process, once an online order is placed, the e-commerce firm will process the order by fetching the items in its warehouse and preparing them to be picked up (or dropped off) by the shipping vendor—a stage we refer to as order processing. Next, the shipping vendor delivers the online order and we refer to this stage as order delivery. Using order tracking tools (e.g., "Order Status" page on a retailer's website or FedEx tracking numbers), customers can view the current status of their order by checking if the order is still being processed or if it is with the shipping vendor. Previous research shows that providing visibility and additional information to customers may improve their experience (Buell et al., 2017). However, because customers are now able to continuously monitor the status of their orders, inefficiencies or delays in the order fulfillment process could become visible and potentially have a negative impact on customers' perception of their orders.

Our research seeks to empirically examine the impact of information related to order processing time and order delivery time on online customer ratings of an order, which are generally considered as indicators of customer satisfaction (Peng et al., 2019). More formally, the first research question that we ask is: *How do initial order processing and delivery times affect online customer ratings on e-commerce platforms?* The answer to this research question may help e-commerce firms understand how customers evaluate the order fulfillment processes before the actual delivery. Furthermore, it may also provide insights on the differential impacts of order processing and delivery times.

Recent developments in logistics tracking technologies also allow e-commerce firms to take advantage of artificial intelligence and machine learning applications to accurately predict the expected time of delivery (Shields, 2018). Given the high expectations of customers for reliable deliveries, the second research question that we examine is: *How does deviation from the promised delivery date impact online customer ratings on e-commerce platforms?* In particular, we analyze the effects of both early delivery and late delivery on online ratings. Early (late) delivery refers to positive (negative) deviation from the promised delivery date, which is represented by the number of days an order was delivered early (late). Prior studies have indeed shown that timely delivery of an order is associated with higher customer loyalty and satisfaction (Heim & Field, 2007; Heim & Sinha, 2001b). Rao, Griffis, and Goldsby (2011) and Peng and Lu (2017) demonstrate that late delivery is negatively associated with future shopping behavior (i.e., order frequency, basket size, and unit price) of customers. In this study, we cross-validate the postulation that late delivery will have a significant impact on customer satisfaction by formally quantifying the impact of delayed delivery on customer ratings.

Whereas the literature on the effects of late delivery is quite rich, research on the effects of early delivery is limited. Peng and Lu (2017) is among the first to analyze the effects of early delivery and find that early delivery may also have a negative impact on customer satisfaction in a business-to-business (B2B) context. Given that business-to-consumer (B2C) and B2B contexts are quite different (Peng & Lu, 2017), the impact of early delivery in B2C contexts remains unclear. Hence, we systematically bridge this important gap in the literature by analyzing how deviations from the promised delivery date, either early delivery or late delivery, affect customer ratings in online marketplaces in a B2C context.

Our next research question investigates whether purchase costs (which include order cost of items and delivery cost) strengthen or mitigate the effect of deviations from the promised delivery date on online ratings. Formally, the third research question that we study is: *Do order and freight costs moderate the relationship between delivery outcomes* (i.e., *early or late deliveries*) *and online ratings on e-commerce platforms?* Answering this question will provide key insights on the interplay among purchase costs, timeliness of delivery, and online customer ratings.

1.2 | Research context

To answer our research questions, we collaborated with an e-commerce firm (firm *ABC*) from South America and obtained transaction level data with information at the order, product, customer, and seller levels as well as customer ratings after purchase. We combine customer, order, seller, and product information to construct a unique data set so that we can empirically examine the relationship between online customer ratings and various aspects of the e-commerce firm's order fulfillment process, including order processing and delivery times, late/early delivery, and purchase/freight costs. We discuss the details of our data in Section 4.

1.3 | Key findings and contributions

With the advancements in Industry 4.0 technologies, e-commerce-firms are increasingly turning to emerging technologies such as IoT, artificial intelligence, and cloud computing to improve their internal operations and provide accurate delivery times (PWC, 2016). Furthermore, retailers are now also expected to provide more detailed information regarding their order fulfillment processes to the customers. While utilizing Industry 4.0 technologies allows retailers to provide information related to order fulfillment to the customers, the consequences of providing such information are not yet studied in the previous literature. In this research, we attempt to fill this important gap in the literature by empirically analyzing how customers process information related to delays in order fulfillment processes.

Resting on expectation-disconfirmation theory (Oliver, 1977), we argue that the observed order fulfillment process (i.e., order processing and delivery times) prior to actual order delivery may affect customers' perception of online shopping experience. Our results indeed reveal that longer order processing and delivery times are associated with lower online ratings. We demonstrate that such effects may exist regardless of the outcome of the order fulfillment process (i.e., whether an order delivery is actually early, late, or on-time). Our results also suggest that early delivery impacts online ratings positively, while late delivery has a negative impact.

Drawing on prior research on attribution theory (Weiner, 2000), we posit and demonstrate that the negative impact of order processing time is greater than that of delivery time because customers tend to believe that a firm has direct control over its order processing operations and therefore should be held more responsible. Hence, e-commerce firms should process online orders as quickly as possible and eliminate inefficiencies or delays in their internal operations. Next, we find that both order value and freight cost moderate the impact of late delivery on online ratings because they may influence how a customer assigns responsibility for late deliveries between the e-commerce firm and the third-party shipping vendor. Similarly, we show that freight cost also moderates the relationship between early delivery and online ratings. Hence, an important managerial implication is that e-commerce firms need to ensure early or on-time delivery especially for high-value items. Finally, we also find curvilinear relationships between online ratings and number of days an online order is late or early. For example, the negative effect of a late delivery follows a convex-shape curve such that its impact decreases as the number of days an online order is late increases. Likewise, the positive effect of an early delivery increases at a decreasing rate as the number of days an online order is early increases.

In addition to the managerial implications that we discussed earlier, our study contributes to the technology management and retail operations literature. While previous literature has mainly documented the impact of various product characteristics on online ratings, our first contribution lies in understanding the impact of order fulfillment processes on customers' assessment of purchases in the form of online ratings. In particular, the rich information contained in our transaction level data allows us to investigate not only the impact of delivery status (i.e., early and late deliveries), but also how order fulfillment processes before the actual delivery (reflected by order processing time and delivery time) influence online ratings. Next, we contribute to the literature by studying the effects of both early and late deliveries on customer satisfaction in a B2C context.

Finally, our study documents the effects of order fulfillment processes on customers' evaluation of an online order in the context of a developing economy. Prior research shows that customers from developed economies may evaluate services differently than those from developing economies (Castaño & Flores, 2019). For instance, customers in developed economies expect e-commerce firms to have efficient logistics processes, and thus expect faster order fulfillment and timely deliveries. However, given the recent emergence of online shopping platforms in developing economies, it is not clear whether customers from these markets also have high service expectations from e-commerce firms in terms of order fulfillment and delivery. Our study fills this important gap in the literature by analyzing the impact of order fulfillment processes on online customer ratings. In doing so, we also contribute to the technology management literature by examining the applicability of expectation-disconfirmation theory in a global context.

The rest of this manuscript is organized as follows. We discuss the relevant literature in the next section. In Section 3, we present the theoretical background and develop our hypotheses. We describe our data, key variables, and empirical methodology in Section 4 and present our findings in Section 5. Next, we discuss a series of robustness checks and alternative model specifications in Section 6 and conduct post-hoc analyses to derive important managerial insights in Section 7 and Section 8. Finally, we discuss insights and implications of our findings in Section 9.

2 | LITERATURE REVIEW

In this section, we position our work with respect to the extant literature on online consumer ratings. While there exists a healthy stream of literature regarding the impact of online ratings on sales (Chevalier & Mayzlin, 2006; Duan et al., 2008; Liu, 2006; Zhu & Zhang, 2010), purchase intentions (Liu et al., 2017), product returns (Minnema et al., 2016; Sahoo et al., 2018), and price differentials between new and remanufactured products (Subramanian & Subramanyam, 2012), the antecedents of online ratings remain largely unclear. Hence, our research examines how logistics processes and other factors influence online customer ratings.

Prior research suggests that logistics processes have significant impacts on customer loyalty and repurchase intentions (Heim & Sinha, 2001b; Wan et al., 2016). Online customer ratings, however, can be considered as the degree of customer satisfaction after an online purchase (Engler et al., 2015). In line with prior research, we consider that order fulfillment processes and delivery performance in supply chains play significant roles in driving customer satisfaction (Lee & Billington, 1992; Stewart, 1995). Stank et al. (1999) show that order fulfillment (operational) performance has a positive impact on customer satisfaction in the fast food industry while Davis-Sramek et al. (2008) presents the same finding in a B2B setting. In a B2C context, Griffis et al. (2012) focus on online retailing and show that purchase satisfaction is positively associated with order fulfillment quality and negatively associated with order cycle time. Note that Griffis et al. (2012) use survey data (791 responses) while our research employs transaction data coupled with online customer ratings.

Using firm-level survey data, Rosenzweig et al. (2003) show that delivery reliability impacts customer satisfaction through mediating the relationship between supply chain integration and customer satisfaction. Similarly, Vaidyanathan and Deveraj (2008) use survey data from 131 purchasing and procurement managers and find that order timeliness (i.e., logistics fulfillment capability) has a positive and significant impact on customer satisfaction. Treating order fulfillment delay as an operational glitch in a B2C context, Rao, Griffis, and Goldsby (2011) show that failure to deliver on the promised date undermines the future shopping behavior of previously loyal customers while increasing customer anxiety. Investigating the drivers of customer satisfaction in public transportation services, Mouwen (2015) shows that on-time performance, travel speed, and service frequency are the most important service attributes for customer satisfaction. In a B2B context, Peng and Lu (2017) investigate the impact of four delivery performance measures—on-time delivery rate, early delivery inaccuracy, late delivery inaccuracy, and delivery speed—on future customer transaction quantities and unit prices as well as the moderating role of customer type. In particular, the authors show that while late delivery is negatively associated with future customer transactions, early delivery does not influence order quantity. Furthermore, the authors also show that on-time delivery is not significantly associated with order quantity.

Our study is different from the existing literature on customer satisfaction in several aspects. First, previous research typically focuses only on late delivery when examining customer satisfaction in online retailing contexts. We investigate the impact of both early delivery and late delivery on online customer ratings (i.e., customer satisfaction). Second, the extant research generally considers only the final outcome of an order fulfillment process (i.e., whether an order is delivered on-time). Using the granular structure of our data, we look into the order fulfillment process before the actual delivery by decoupling the initial order processing time from the total delivery time. In doing so, we not only explore the impact of both initial order processing and total delivery times on online customer ratings but also compare their marginal effects. Third, we investigate the moderating roles of order cost and freight cost on the relationship between early and late deliveries and online customer ratings. Finally, the fact that we conduct our analyses using a data set obtained from a developing country in South America gives us a unique opportunity to contribute to the body of knowledge in this domain by checking whether previously identified impacts of order fulfillment processes on customer satisfaction (e.g., the impact of late delivery on customer satisfaction) are generalizable in a global context.

3 | THEORY AND HYPOTHESES

Expectation-disconfirmation theory (EDT) posits that an individual's level of satisfaction is driven by the relative relationship between his/her (we use *her* hereafter in this section for brevity) prior expectations and the observed outcome (Oliver, 1977; Venkatesh & Goyal, 2010). Disconfirmation occurs when expectations and outcome are mismatched. An outcome exceeding expectations generally leads to positive disconfirmation, which then results in increased satisfaction. When the outcome does not meet the expectations, however, an individual will experience negative disconfirmation of her prior expectations and will therefore be dissatisfied with the experience.

EDT has been widely adopted in marketing and information system research in examining the efficacy of technology adoption and customer satisfaction (Chen et al., 2018). In a retail operations context, a customer forms a level of satisfaction about her shopping experience based on prior expectations about the experience and the actual outcome. Prior expectations can be defined as a customer's a priori belief about the various aspects of her shopping experience. Given the context of our research, and resting on Zeithaml et al. (1993) and Thirumalai and Sinha (2005), we consider expectations as standards a customer holds for a retailer during an online purchase in terms of its order fulfillment process, specifically in terms of speed and timeliness. A number of studies suggest that negative disconfirmation of a customer's prior expectations will result in decreased satisfaction (e.g., Churchill & Surprenant, 1982; Oliver, 1980; Spreng & Page, 2003).

The use of online logistics tracking technologies may lead to several theoretical nuances in examining online customer satisfaction from the theoretical lens of EDT. First, online retailing can be different from the traditional retail settings because it involves a delivery process such that customers need to wait for the actual delivery after they place online orders. Online retailing entails not only the physical product being sold but also the process that facilitates the purchase of the product (Heim & Sinha, 2001a). As a result, a customer's level of satisfaction will also be determined by both the product and the process that involves activities such as shopping, purchase, and delivery (Zeithaml, 2000). The availability of logistics tracking technologies allows customers to receive transparent and timely updates throughout the order fulfillment process. Therefore, the performance of such a fulfillment process is essential in establishing a satisfactory online shopping experience, as customers can closely monitor the process in which their orders are handled and delivered (Iqbal et al., 2003).

Second and more importantly, the extant research through the theoretical lens of EDT typically assumes that an individual follows a chronological process when evaluating the observed outcomes against her prior expectations (Bhattacherjee, 2001). In particular, the customer may (1) form her prior expectations regarding the shopping experience, (2) observe the outcome and form a perceived level of performance, (3) evaluate whether her expectations are disconfirmed given the actual outcome, and (4) form her level of satisfaction/dissatisfaction as a function of prior expectations and disconfirmation (Oliver, 1980). Traditionally, when the status of an order during the fulfillment process is not readily visible to a customer, she may not have the opportunity to explicitly evaluate the actual outcome against her prior expectations until observing an actual delivery (Griffis et al., 2012). The evaluation of expectations will occur only at the end of the order fulfillment process in such a context, because the only actual outcome a customer observes (with regard to the speed and timeliness of the order fulfillment process) is the time when she receives the order. Customers face asymmetric information during online shopping as they can only estimate the expected (not the actual) delivery performance before the purchase is completed (Rabinovich & Bailey, 2004).

Nevertheless, we argue that detailed information about order processing time and delivery time available to customers prior to actual delivery reduces such information asymmetry and therefore creates additional opportunities for customers to evaluate the status of their order against their prior expectations. In other words, when order processing and delivery information is available, a customer can observe multiple, up-to-date waves of information regarding the order fulfillment process before actually receiving the order. As a result, the customer may consider the update information that tracks the order fulfillment process as indicators of delivery performance and evaluate them against her prior expectations. Previous research has found evidence that customers actively gather and evaluate information received throughout a service encounter (Coye, 2004; Hamer et al., 1999; Rust et al., 1999). As a result, it is possible that the customer may actively observe how her order is being handled in terms of order processing and delivery and evaluate such information against her prior expectations, before the order is actually delivered.

Customers generally possess a certain level of expectation for the service process they receive in terms of delivery speed so that their needs are satisfied promptly (Greenberg, 2010; Ho & Zheng, 2004; Kostami & Rajagopalan, 2014). In a service context, faster delivery speed is positively associated with customer satisfaction (Yang et al., 2015) because it signifies service efficiency (Ding et al., 2007). This relationship has also been shown to hold in online settings (Ding et al., 2011; Parasuraman et al., 2005). Customers often feel anxious after placing an order on an online platform until they lay their hands on the purchased product (Peck & Childers, 2003; Rao, Griffis, & Goldsby, 2011). Thus, observing longer order processing time and delivery time may violate a customer's expectations because she may be concerned about the risks associated with the order fulfillment process such as uncertainty about the delivery time and whether the right items have been shipped (Burke, 2002; Otim & Grover, 2006). Furthermore, numerous news sources and industry reports provide anecdotal evidence suggesting that customers expect fast delivery when making online purchases (e.g., Convey, 2019).

Taken together, customers may have pre-existing expectations about an e-commerce firm's order fulfillment process in terms of order processing time and delivery time (Thirumalai & Sinha, 2005) before making purchases. The availability of logistics tracking technologies may result in opportunities for customers to evaluate the order fulfillment process against these prior expectations before actually receiving the delivery. Therefore, negative expectation disconfirmation may occur when a customer observes updates available through logistics tracking technologies that indicate order processing and/or delivery times that are too long compared to her prior expectations. Although online customers may have varying expectations with regard to the order fulfillment process, the likelihood of expectation disconfirmation becomes higher as order processing time and delivery time increase, because customers generally consider faster order delivery desirable. Online customer ratings will therefore be negatively affected, regardless of whether or not the order delivery is actually delayed in the end.

Hypothesis 1a (H1a). *Longer order processing time is negatively associated with online customer ratings.*

Hypothesis 1b (H1b). *Longer delivery time is negatively associated with online customer ratings.*

While a customer may have experienced expectation disconfirmation from merely observing longer than expected order processing and delivery times, the time the order is actually delivered may create another opportunity for him/her to evaluate the final delivery time against her prior expectation about the order delivery time. As e-commerce firms increasingly utilize advanced predictive technologies to provide estimated delivery dates, a customer's expectations about the final delivery time can be more specific and salient. Customers often consider late delivery of their online orders as service failures by the retailers (Rao, Griffis, & Goldsby, 2011). Such service failures may in turn result in lowered satisfaction levels due to negative expectation disconfirmation (Smith & Bolton, 1998).

Moreover, early research on EDT originally posits that prior expectations and disconfirmation are the only determinants of satisfaction (Venkatesh & Goyal, 2010). However, subsequent research suggests that the actual outcome has independent effects on satisfaction, in addition to its indirect impact through disconfirmation of prior expectations (Churchill & Surprenant, 1982). In the context of our study, such an independent direct effect suggests that the actual outcome (i.e., potential late deliveries) may negatively affect customer satisfaction, even after a customer experiences negative disconfirmation resulting from observing longer than expected order processing and delivery times through logistics tracking technologies.

Previous studies have indeed found that on-time delivery is a key driving factor of customer satisfaction (Boyer & Hult, 2005; Lee & Whang, 2001). While consistent on-time delivery will lead to increased future sales and customer satisfaction (Fisher et al., 2019; Harris et al., 2006; Rosenzweig et al., 2003), late delivery of orders may lead to customer dissatisfaction and negatively affect future sales (Rao, Griffis, & Goldsby, 2011). Therefore, aligning with the extant literature, we expect that the number of days an order delivery is delayed will be negatively associated with customer satisfaction, which is reflected by online customer ratings.

Hypothesis 2a (H2a). *A negative deviation from the promised delivered date (i.e., late delivery) is negatively associated with online customer ratings.*

Prior research on reference dependence suggests that the impact of positive or negative disconfirmation may differ because customers generally react to a gain or a loss situation differently (Tereyağoğlu et al., 2018). Compared to late delivery, early delivery represents an opposite situation where an order is delivered before the promised delivery date. Peng and Lu (2017) argue that early delivery, just as late delivery, also signifies a deviation within a firm's order fulfillment process between the promised delivery time and the actual delivery time. Early delivery may have a potentially negative impact on customer satisfaction in a business-to-business (B2B) context because it may distort a buyer's operations in terms of inventory management and production planning, among others (Peng & Lu, 2017). Thus, from an EDT perspective, both late and early delivery may lead to negative disconfirmation of customer's expectation.

We posit that the impact of early delivery may be different in an online retail setting because the role of the order fulfillment process is manifested differently between B2B and B2C settings (Rao, Goldsby, et al., 2011). Online retail orders tend to be impulsive and unplanned, whereas B2B purchases are generally planned and continual (Agatz et al., 2008). Compared to B2B supply chains that involve repeated and interpersonal interactions between sellers and buyers, the order fulfillment process in B2C contexts is focused solely on the physical delivery of the items (Rabinovich & Bailey, 2004). As a result, online customers tend to evaluate the order fulfillment process based on their experience with the order delivery itself, especially in terms of timeliness (Rabinovich & Bailey, 2004; Yang & Jun, 2002). In this case, early delivery may strongly indicate that an e-commerce firm outperforms itself in the order fulfillment process so that the order is delivered before the promised date. Such a better-than-expected outcome may therefore lead to positive disconfirmation of online customers' expectations regarding the order fulfillment process (Venkatesh & Goyal, 2010).

The extant literature indeed suggests that faster delivery of online orders leads to heightened customer evaluation of the shopping experience because it effectively reduces transaction costs of online shopping through quicker gratification (Balasubramanian, 1998; Fisher et al., 2019). Shortened order delivery time is therefore associated with favorable evaluation of the order fulfillment process and subsequently improves online customer satisfaction (Griffis et al., 2012). Accordingly, we expect that early delivery by e-commerce firms may be viewed favorably by customers and subsequently result in positive disconfirmation of their expectations. Thus, the number of days an order is delivered early may be positively associated with online customer ratings.

Hypothesis 2b (H2b). *A positive deviation from the promised delivered date (i.e., early delivery) is positively associated with online customer ratings.*

Prior research demonstrates that attributions of responsibilities play an important role in moderating the impact of expectation disconfirmation on customer satisfaction (Tsiros et al., 2004). Attribution theory suggests that individuals seek to make sense of the world by attributing causes to events (Hartmann & Moeller, 2014). These attributions then affect individuals' feelings, expectations, and future behaviors. Such an attribution process is particularly salient when an individual responds to negative outcomes (Folkes, 1984; Rozin & Royzman, 2001; Tomlinson & Mayer, 2009). The attribution of causes is usually evaluated along three dimensions: stability, controllability, and locus of causality (Russell, 1982). Among these dimensions, stability is less related to our research context as it is concerned with whether a particular cause is temporary or permanent.

In a retail context, controllability refers to the degree to which a customer believes that a retailer could impact or prevent the occurrence of a failure (Hess et al., 2003). It may also be conceptualized as a retailer's influence over potential problems and outcomes (Hartmann & Moeller, 2014). Controllability is an important moderating factor in the relationship between service failures and customer satisfaction. A customer generally attributes more responsibility to the retailer when she believes that the retailer has control over a potentially negative outcome (Choi & Mattila, 2008).

In the context of our study, the e-commerce firm and its sellers first process the orders by preparing the items to be dropped off at the shipping vendor location (i.e., order processing). From the customers' perspective, this stage of the order fulfillment process is considered internal as it is handled by the e-commerce firm and its sellers. Thus, order processing time reflects the efficiency and timeliness of the retailer, which has direct control over its operations. Once orders are processed, sellers use the shipping labels created by the e-commerce firm and hand the orders over to a third-party courier to complete the delivery (i.e., order delivery). As a result, the delivery of the items can be considered largely external to the e-commerce firm, who may only exert limited control over how fast the items will be delivered by the shipping vendor (delivery time) (Bolumole, 2001). Therefore, customers may generally believe that a retailer's level of controllability is higher for order processing time than for delivery time.

Research on attribution theory suggests that customers assign more weight to internal causes than to external causes when evaluating a product/service because a retailer has a higher level of controllability over internal operations (Brickman et al., 1975). Logistics tracking technologies relay granular information to customers regarding the order fulfillment process including order processing time and delivery time. Consequently, customers are able to differentiate between a retailer's internal order processing and an external shipping vendor's delivery process when evaluating the overall order fulfillment performance. Thus, we expect that the negative impact of longer order processing time on customer satisfaction (reflected by online ratings) will be larger than that of delivery time, because customers may consider order processing activities internal and therefore more controllable by the retailer.

Hypothesis 3 (H3). *The negative impact of order processing time on online customer ratings is larger than that of delivery time.*

Locus of causality is another aspect of attribution theory that describes where the perceived cause of observed outcome is located in the order fulfillment process, which can be either with the retailer or with the third-party shipping vendor (Oflaç et al., 2012). When a delivery is delayed, customers are naturally motivated to understand the causes behind such a negative outcome and attribute responsibilities accordingly (Sloman & Lagnado, 2015; Weiner, 2000). Therefore, when an online order is not delivered on-time, a customer may engage in a process of apportioning blame according to the locus of causality between the retailer and the third-party shipping vendor that handles the physical delivery (Crant & Bateman, 1993; Pallas et al., 2018). Such attribution of blame may then moderate how the customer responds to the late delivery, potentially in the form of online ratings (Bower & Maxham III, 2012).

The extant literature suggests that price partitioning may play an essential role in determining where the locus of causality is placed between the retailer and the third-party shipping vendor (Pallas et al., 2018). Price partitioning refers to a situation where a retailer partitions the total price of an order into a set of separate charges (Bertini & Wathieu, 2008). In our study, the total price a customer pays during an online purchase is partitioned into two parts, namely order cost (i.e., the cost of items being purchased) and freight cost. The partitioning of total price between order cost and freight cost may induce a customer to separate her assessment of the purchased items from that of the delivery process (Hamilton & Srivastava, 2008). Higher costs are generally associated with customers' more stringent expectations (Zeithaml et al., 1993). Thus, the magnitude of the order cost and freight cost together may influence how a customer divides her attention when an order is delayed (Chakravarti et al., 2002).

While customers often view the physical delivery of their orders as an inseparable part of the shopping experience an e-commerce firm offers, they may shift the focus of their attribution of delays in order fulfillment when a third-party shipping vendor is involved (Oflaç et al., 2012). Through an experimental study, Oflaç et al. (2012) differentiate between an e-commerce firm's main offering (i.e., the product or service sold) and supplementary service, which is the logistics delivery service offered by a third-party courier. The study demonstrates that customers attribute the causes of delayed deliveries (and blame) to retailers and couriers separately. In particular, a retailer's use of a third-party courier may shift a customer's attribution of delivery delays towards the courier. Correspondingly, the blame attributed to the retailer may be mitigated because it is seen as more excusable since an external third-party courier is responsible for the delivery of the order (Folkes & Kotsos, 1986; Gilbert et al., 1988).

In addition, freight cost is considered a type of surcharge a retailer imposes on customers, which is separate from the base price (i.e., the order cost of the purchased items themselves). Prior research further demonstrates that customers are sensitive to order cost and surcharges (Akturk & Ketzenberg, 2022a, 2022b; Bolton et al., 2003). Surcharge information, including freight cost, may affect locus of causality such that the third-party shipping vendor (rather than the retailer) will receive more blame because it is considered an external third party (Pallas et al., 2018). As such, when an order is delayed, the blame attributed by a customer may be effectively shifted away from the retailer towards the third-party shipping vendor as the freight cost increases.

Overall, we expect that the negative impact of the number of days an order is delivered late on online customer ratings is moderated by a customer's attribution of such a failure. More specifically, we posit that higher order cost may shift the locus of causality towards the retailer. As a result, the negative impact of the number of days an order is delivered late on a customer's satisfaction with the retailer is strengthened. Higher freight cost, however, may shift the locus of causality away from the retailer and towards the third-party courier, thereby attenuating such a negative relationship.

Hypothesis 4a (H4a). *Order cost amplifies the negative impact of the number of days an order is delivered late on online customer ratings.*

Hypothesis 4b (H4b). *Freight cost attenuates the negative impact of the number of days an order is delivered late on online customer ratings.*

Following a similar logic, we expect that order cost and freight cost may also influence the locus of causality in the event of early delivery and subsequently moderate the relationship between early delivery and customer satisfaction. Research on attribution theory indeed posits that individuals actively process information and seek to make causal inference in explaining both success and failure (Oflaç et al., 2012). Therefore, attribution may also occur in situations where early delivery of online orders results in positive disconfirmation of an online customer's prior expectations (Tom & Lucey, 1995).

On the one hand, higher order cost may shift the locus of causality towards the retailer because it increases a customer's expectations (Oliver, 2014). Previous research finds that positive disconfirmation may generate a higher level of satisfaction when an individual's prior expectations are higher (Oliver, 1977; Olshavsky & Miller, 1972). Oliver (1977) further argues that an individual with higher expectations may be induced to believe that an outcome exceeds her expectations, even if such a perception is not necessarily accurate. As a result, the relationship between positive disconfirmation and satisfaction may be more salient in situations where a customer perceives the retailer to be more responsible for an early delivery.

On the other hand, the extant research also finds that the impact of a positive outcome on customer satisfaction is stronger when the customer attributes the outcome to internal causes compared to external causes (Oliver & DeSarbo, 1988). When attributing the causes of early delivery, locus of causality may affect whether an online customer believes that such a positive outcome was driven by internal causes (i.e., the retailer) or external causes (the third-party courier) (Pallas et al., 2018). Freight cost serves as a surcharge that covers the cost the e-commerce firm incurs to deliver the orders through an external shipping courier. When freight cost increases, the locus of causality in the event of early delivery may be shifted away from the retailer. In this case, the relationship between positive disconfirmation due to early delivery and customer satisfaction may be attenuated (Tsiros et al., 2004).

Taken together, because order cost and freight cost may affect a customer's perceived locus of causality and subsequently her attribution of an early delivery, we expect that the impact of the number of days an order is

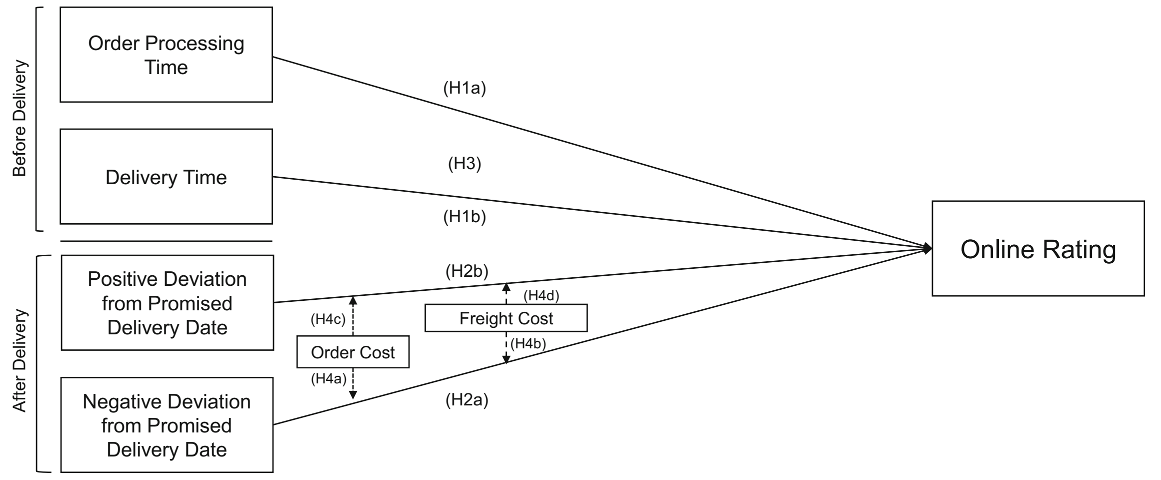

FIGURE 1 Research model

delivered early on online customer ratings may be heightened by higher order cost because it may shift the locus of causality towards the retailer. Higher freight cost, however, may shift the locus of causality away from the retailer and attenuate the positive impact of the number of days an order is delivered early on customer ratings.

> **Hypothesis 4c (H4c).** *Order cost amplifies the positive impact of the number of days an order is delivered early on online customer ratings.*

> **Hypothesis 4d (H4d).** *Freight cost attenuates the positive impact of the number of days an order is delivered early on online customer ratings.*

We summarize and present our research framework in Figure 1.

4 | DATA AND EMPIRICAL MODEL

The main objective of our study is to analyze the effects of various aspects of the order fulfillment process on customer perceptions measured as online customer ratings. In doing so, we employ data from an e-commerce firm (i.e., firm *ABC*) from South America. Firm *ABC* owns contracts from thousands of sellers and helps them increase their customer base in the marketplaces. Online customers see only the e-commerce firm as the seller and make their purchasing decisions accordingly. Once the purchase transaction is completed, the e-commerce firm selects a seller to fulfill the order. Because the e-commerce firm also owns contracts with the Post Office, it sends shipping labels to sellers in order to standardize the delivery process.

The data set from the e-commerce firm includes 93,131 transactions and spans 23 months from October 2016 to August 2018. The data that we use in this study is a randomly sampled subset of orders placed by customers on the e-commerce firm's website that received an online rating. In a meeting with the e-commerce firm's managers, we confirmed that these randomly selected observations constitute a representative sample of the whole data set (we also validate that the distribution of the sample data is consistent with other studies examining customer ratings and we discuss this in Section 4.1). Furthermore, during the order fulfillment process, customers can check the current status of their online orders (e.g., if the order was processed, shipped, or delivered). The data contains information related to order processing time, delivery time, early/late delivery, order cost, freight costs, and ratings, which enables us to investigate the impact of logistics processes on online rating. In the rest of this section, we discuss the operationalization of the dependent variable, key independent variables, and control variables incorporated in our empirical analyses. A description and summary statistics of the key variables are provided in Table 1.

4.1 | Variables

Dependent variable: The dependent variable in our study is the online rating provided by the customer for an order (denoted by *Rating*).[1] These follow a star-rating scheme in which 5-star denotes the highest level of satisfaction and 1-star denotes the lowest level of satisfaction. The mean ratings for all the orders in our sample is 4.14. Our data consists of 9316 orders with 1-star ratings; 2883 orders with 2-star ratings; 7778 orders with 3-star ratings; 18,283 orders with 4-star ratings; and 54,871 orders with

TABLE 1 Summary statistics for key variables

Variables	Description	Mean	SD	Min	Max
Dependent variable					
Rating	Online customer ratings	4.14	1.29	1	5
Independent and moderating variables					
ProcessingTime	Time taken by the firm to process the order (days)	3.22	3.56	0	107
EarlyDays	Number of days an order was delivered prior to the promised date (days)	12.42	7.62	0	42
DelayDays	Number of days an order was delivered after the promised date (days)	0.73	4.68	0	188
Late (Binary)	=1 if delivered after the promised delivery date, else 0	0.07	0.25	0	1
OnTime (Binary)	=1 if delivered anytime on the promised delivery date, else 0	0.014	0.12	0	1
DeliveryTime	Time taken by the logistics partner to deliver the order (days)	9.31	8.79	1	205
OrderValue	Total cost of all items in the order	137.23	209.69	0.85	13,440
FreightCost	Total freight cost for the order	22.79	21.64	0	1794.96
Control variables					
Weight	Product weight measured in grams	2117.26	3769.31	0	40,425
Volume	Product volume measured in cm^3	15,313.23	23,489.45	168	296,208
Photos	Number of images of the product on e-commerce firm's website	2.25	1.74	1	20
PaymentMethods	Number of different methods used to pay for the order	1.04	0.37	1	26
Payment Installments	Number of installments taken by the customer to pay for the order	2.93	2.72	0	24
OrderItems	Number of items in the order	1.14	0.54	1	21
RatingDelay	Number of days between the date of rating and delivery date	0.42	4.72	−186	89
DescriptionLength	Length of the description of item on the e-commerce platform	794.42	655.18	4	3992
Average CategoryScore	Cumulative average rating for the product category	4.15	0.062	2.77	4.46
SingleSeller (Binary)	=1 if single seller fulfills the order, else 0	0.99	0.11	0	1
SingleProduct (Binary)	=1 if the order contains single product, else 0	0.97	0.18	0	1
RepeatCustomer (Binary)	=1 if repeat customer, else 0	0.032	0.18	0	1

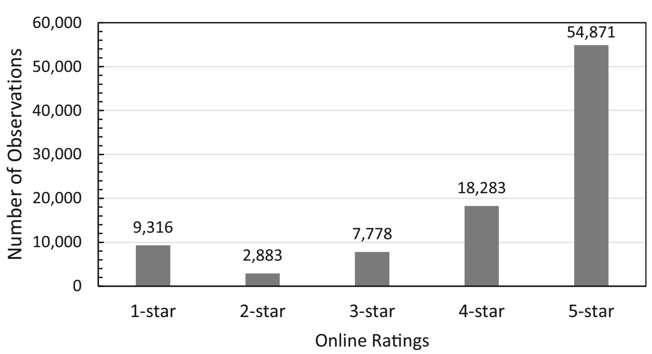

FIGURE 2 Online ratings distribution

5-star ratings. The distribution of the customer ratings is provided in Figure 2. The J-shaped distribution of the observed ratings in our data is consistent with observations from prior studies (Hu et al., 2009; Ko et al., 2019; Kumar et al., 2018), which provides additional support that the data is representative of the underlying population data regarding customer ratings.

Main explanatory and moderating variables: The first set of key variables of interest in our study are related to the time taken by the e-commerce firm to complete the order fulfillment processes. The variable *ProcessingTime* represents the total time taken by the e-commerce firm to process the order placed by the customer. Specifically, it captures the number of days between when the order is dropped off at the shipping vendor's location and the order purchase date (i.e., when the customer placed the order). Next, *DeliveryTime* denotes the total number of days the shipping vendor took to deliver the order to the customer after receiving it from the firm. Figure 3 provides an illustration of the e-commerce firm's order fulfillment process and the operationalization of our main variables of interest.

When a customer places an order, the e-commerce firm provides an estimated date of order delivery. The second set of variables of interest are related to deviation from the promised delivery date. In particular, the variable *DelayDays* captures the negative deviation from the promised delivery date, that is, the number of days an order was delivered after the promised delivery date. In our data, we observe that 6372 (6.84%) of the orders were delivered late. This is within the industry average of 5%–15% of online orders that are delivered to the customers late (Premack, 2019), which further provides support to suggest that our sample is a good representation of population data.

Similarly, *EarlyDays* denotes the positive deviation from the promised delivery date. Specifically, this variable captures the number of days an order was delivered prior to the promised date. While the primary focus of our study is on estimating the impact of the length of deviation from the promised delivery time on online ratings, in Section 8, we extend our analysis to analyze the impact of timeliness of a delivery (i.e., whether the order was either early or late) on ratings.

Hypotheses H4a and H4b posit that order cost and freight cost influence how customers evaluate late or early delivery. To test these hypotheses, we include *OrderValue* and *FreightCost* as the moderating variables in our model. *OrderValue* measures the total purchase price of the items combined, and *FreightCost* denotes the total shipping fee charged to customers.

Control variables: In addition to the main variables, we employ a wide variety of control variables to capture product- and customer-specific features that could impact the online ratings. To capture customer-related heterogeneity, following earlier literature (e.g., Mallipeddi et al., 2021), we control for customers' geographical location using region-wise dummy variables, which allow us to account for any time-invariant and spatially-correlated unobservables. Next, a customer's rating might be targeted towards the product quality or the order fulfillment quality. To account for this customer-related heterogeneity, we rely on three control variables. First, we control for the average online ratings for all products within the same category, which could affect the expectations of the customer (denoted by *AverageCategoryScore*, which represents prior ratings).[2] Second, we argue that when a customer leaves a rating right after she receives the order, it could reflect the customer's evaluation of process quality. On the other hand, if the customer takes time to leave a rating, it could imply that the customer had time to experience the product quality and hence this rating reflects the product quality. Therefore, we control for the delay in a customer posting the rating using *RatingDelay* variable,[3] which is operationalized by the time difference in terms of days between when the online rating was posted for an order and when the order was actually delivered. Third, we also control for repeat customers using a binary variable, *RepeatCustomer*.

Previous literature has argued that customers' payment methods may influence their evaluation of service (e.g., Field et al., 2004). We control for this potential source of heterogeneity by controlling for payment method used by the customer when placing the order, number of payment methods used to place an order (note that a few customers used multiple payment methods to place an order), and whether the customer purchased the product with a payment installment plan. More specifically, customers may have completed an online transaction using different payment methods such as credit card, debit card, and Boleto tickets (a push-payment system commonly used in South America). We control for payment methods by adding corresponding binary variables.

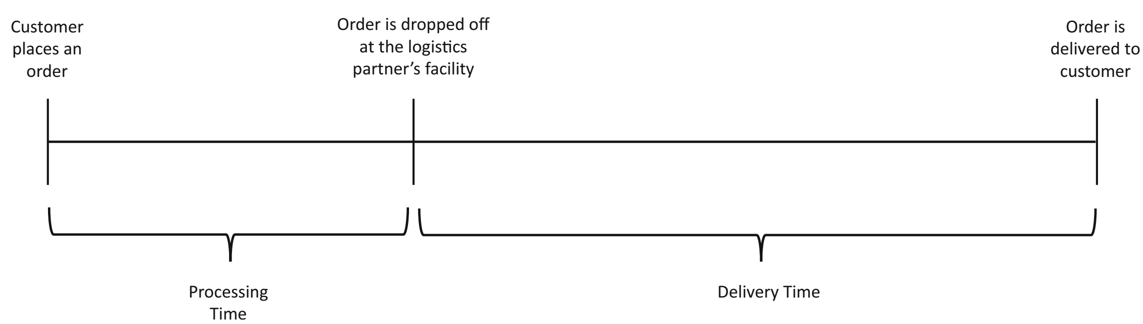

FIGURE 3 An illustration of the order fulfillment process

In addition, we include the number of installments as an additional control variable since customers have the option to make their payments in installments (operationalized by *PaymentInstallments* variable).

To control for any heterogeneity in order characteristics, we include the following control variables in our model: *OrderItems*, *SingleSeller*, and *SingleProduct*. *OrderItems* accounts for the total number of items in the order and our data show that more than 90% of the orders have single items. Next, *SingleSeller* is a binary variable denoting whether the order is fulfilled by a single seller or multiple sellers, and our data shows that more than 98.7% of the orders are fulfilled by a single seller. *SingleProduct* is a binary variable that is set to =1 if the order comprises of only a single product, which is the case for more than 96.7% of orders in our data.

We also account for product-related heterogeneity by controlling for product weight, product volume, number of product-related images on the shopping platform, the description length, and product category. Our data consist of products from a wide-range of categories including, auto and industrial, books, electronics, fashion, home goods, office products, and general utilities. Specifically, 7888 (8.47%) observations belong to the auto and industrial category; 964 (1.04%) observations belong to the books category; 22,297 (23.94%) observations belong to the electronics category; 7114 (7.64%) observations belong to the fashion category; 43,013 (46.19%) belong to the home goods category; 6083 (6.53%) belong to the office products category; and 5772 (6.20%) observations belong to the general utilities categories. To control for heterogeneity at the product-level, we include binary variables for each product category. Please see Table A1 in the Appendix for summary statistics regarding product categories. Note that if there are multiple products in the order, we use the product category for the most expensive product in the order, as this product could influence customers' evaluation of the entire order. Finally, to account for time fixed effects, we include year and month dummy variables, which enable us to account for any exogenous time-specific shocks.

4.2 | Empirical model and estimation

In Hypothesis H1a, we posit that longer order processing time is negatively associated with the online ratings. Similarly, we expect a negative relationship between longer delivery time and online ratings (H1b). The hypothesis that the impact of order processing time is larger than that of delivery time (H3) can then be examined by comparing the corresponding coefficients estimated by the model. We then posit in H2a (H2b) that a late (early) delivery of an order would, on average, have a negative (positive) effect on the rating for an order. We also predict that the order value and freight cost will moderate the effects of late (early) delivery on online ratings respectively.

As discussed earlier, the dependent variable in our model is the online customer rating for each order in our data set. Consistent with prior literature (Perdikaki et al., 2015; Wu et al., 2021), we employ an ordered logit model to estimate the impact of the variables of interest on online ratings. Nevertheless, for completeness, we supplement our main analysis using a log-transformed linear model and Tobit regression model, consistent with prior literature (Ko et al., 2019; Kumar et al., 2018).

To test our hypotheses, we model the impact of the order fulfillment process on online rating for an order i as follows:

$$
\begin{aligned}
\Pr(Rating_i = k) &= \Pr\left(\alpha_{k-1} < y_i^* < \alpha_k\right) \\
y_i^* &= \beta_0 + \beta_1 EarlyDays_i + \beta_2 DelayDays_i + \beta_3 ProcessingTime_i + \beta_4 DeliveryTime_i \\
&\quad + \beta_5 EarlyDays_i \times OrderValue_i + \beta_6 EarlyDays_i \times FreightCost_i \\
&\quad + \beta_7 DelayDays_i \times OrderValue_i + \beta_8 DelayDays_i \times FreightCost_i \\
&\quad + \beta_9 OrderValue_i + \beta_{10} FreightCost_i + \mathbb{Z}\mathbb{C}_i + \epsilon_i,
\end{aligned}
\tag{1}
$$

where y_i^* is the continuous latent variable, $k \in [1, 5]$ is the realized value of rating, and α_{k-1} and α_k are the thresholds. β_1 and β_2 are the parameter estimates of variables *EarlyDays* and *DelayDays* respectively, which specify the marginal effects of positive/negative deviation length on online ratings. The effects of order processing and delivery times are captured by coefficients β_3 and β_4, respectively. Furthermore, the interaction terms *EarlyDays* × *OrderValue* and *EarlyDays* × *FreightCost* (*DelayDays* × *OrderValue* and *DelayDays* × *FreightCost*) capture the moderating effects of order cost and freight cost on the relationship between *EarlyDays* (*DelayDays*) and *Ratings*. The parameter estimates β_5 through β_8 quantify the direction of the moderating effects of order cost and freight cost. Note that Equation (1) also includes all control variables discussed in Section 4.1. Vector $\mathbb{C}$ denotes all the control variables that account for time-invariant, customer, seller, and product related heterogeneity, while $\mathbb{Z}$ denotes the parameter estimates for the control variables.

5 | RESULTS

The parameter estimates of coefficients for the proposed ordered logit model in Equation (1) are reported in Table 2. Note that to alleviate concerns of outliers affecting the results, we removed 1% of observations from the right side of the distribution for *EarlyDays* and *DelayDays* variables.[4] We first report the parameter estimates of the model without the interaction terms (see Column 1). In Column 2 of Table 2, the estimates of the model with both the main effects and interaction effects are presented. In all our models, we account for heterogeneity in customer, seller, and product features through control variables as we discussed previously. Furthermore, to alleviate potential concerns regarding the failure to meet standard regression assumptions (e.g., i.i.d. errors), we account for heteroskedastic random errors and report robust standard errors in Table 2 and all subsequent tables.

For brevity, the rest of the discussion below focuses on the parameter estimates obtained for the full model, which include both the main and interaction effects. The results indicate that longer order processing time is associated with lower customer ratings. Furthermore, there is a statistically significant negative relationship between delivery time and customer ratings. Thus, these results provide strong support for H1a and H1b, which indicate that irrespective of the timeliness of the actual delivery of an order, both order processing and delivery times can negatively impact customers' perception of the order. Hypothesis 3 posits that the negative impact of order processing time on online ratings (β_3) is larger than that of delivery time (β_4). Our results suggest that the magnitude of β_3 is indeed significantly larger than β_4, thereby supporting H3.[5]

We find that *DelayDays* (i.e., the number of days an order is delivered late) has a negative and significant effect on the customer's rating for the order (p-value <.001), which supports H2a. Next, as postulated in H2b, our parameter estimates suggest that *EarlyDays* (i.e., the number of days an order is delivered early) has a positive and significant effect on ratings (p-value <.001). With respect to the moderating roles of order cost and freight cost, the estimates of the empirical model suggest that the coefficient of the interaction between *DelayDays* and *OrderValue* is negative and significant (with p-value <.001). This result indicates that the negative effect of *DelayDays* on *Rating* is further amplified as the order cost increases, which supports H4a. Furthermore, our results reveal that the coefficient of the interaction between *EarlyDays* and *OrderValue* is positive but not statistically significant, which indicates no significant effect of order costs on the relationship between early delivery on online ratings.

Next, we find that the coefficient of the interaction between *DelayDays* and *FreightCost* is positive and statistically significant (with p-value <.1). This finding reveals that higher freight cost lessens the negative effect of *DelayDays* on customers' ratings, which provides strong support for H4b. Finally, we find that the coefficient of the interaction between *EarlyDays* and *FreightCost* is negative and significant, which indicates that the higher freight costs reduces the positive impact of positive deviation from promised delivery date (i.e., early delivery) on customer ratings. Hence, H4d is supported.

As discussed earlier, for completeness and following prior literature (Ko et al., 2019; Kumar et al., 2018), we supplement our main analysis using a log-linear model, that is, we log transform the dependent variable, *Rating*. The estimates of the log-linear model are presented in Columns 3 and 4 of Table 2. These findings continue to show that *ProcessingTime*, *DeliveryTime*, and *DelayDays* have a negative and statistically significant effect on *Ratings*. Similar to our earlier findings, *EarlyDays* has a positive and significant effect on *Ratings* and *FreightCost* lessens the positive effect of early delivery. Furthermore, the results continue to show that *OrderValue* amplifies the negative effect of delivery after the promised date while *FreightCost* lessens it.

6 | ROBUSTNESS AND SUPPLEMENTARY ANALYSES

We perform a series of additional analyses to verify the robustness of our main results against potential endogeneity concerns and alternative model specifications. We elaborate on each of these checks in the rest of this section.

6.1 | Potential endogeneity concerns

A key concern in the model presented in Equation (1) is the presence of potential endogeneity. Although we control for various customer-, product-, and delivery-related factors, unobserved factors related to the seller might affect when the order is delivered with respect to the

TABLE 2 Parameter estimates: The impact of operations and logistics process on ratings

	Ordered logit model		Log-linear model	
	(1)	(2)	(3)	(4)
	Ratings	*Ratings*	*ln(Ratings)*	*ln(Ratings)*
ProcessingTime	−0.0601***	−0.0596***	−0.0128***	−0.0127***
	(0.00228)	(0.00229)	(0.000574)	(0.000575)
DeliveryTime	−0.0486***	−0.0490***	−0.00922***	−0.00930***
	(0.00162)	(0.00163)	(0.000376)	(0.000378)
DelayDays	−0.246***	−0.248***	−0.0769***	−0.0790***
	(0.00810)	(0.0126)	(0.00182)	(0.00246)
EarlyDays	0.00898***	0.0130***	0.00187***	0.00258***
	(0.00126)	(0.00179)	(0.000268)	(0.000387)
EarlyDays × OrderValue		0.00000306		0.000000135
		(0.00000618)		(0.00000137)
EarlyDays × FreightCost		−0.000187**		−0.0000308*
		(0.0000596)		(0.0000146)
DelayDays × OrderValue		−0.000124***		−0.0000145**
		(0.0000359)		(0.00000462)
DelayDays × FreightCost		0.000792+		0.000170*
		(0.000426)		(0.0000737)
OrderValue	0.0000470	0.0000489	−0.0000137	−0.00000842
	(0.0000419)	(0.0000924)	(9.23e-06)	(0.0000202)
FreightCost	0.000467	0.00270**	0.0000665	0.000394
	(0.000555)	(0.00103)	(0.000137)	(0.000255)
Weight	−6.58e-06*	−6.97e-06*	−4.56e-07	−5.21e-07
	(3.22e-06)	(3.27e-06)	(7.36e-07)	(7.44e-07)
Volume	4.86e-07	4.06e-07	1.70e-08	1.27e-09
	(5.13e-07)	(5.16e-07)	(1.16e-07)	(1.17e-07)
Photos	−0.00884*	−0.00855*	−0.0000328	−2.89e-06
	(0.00389)	(0.00389)	(0.000812)	(0.000812)
PaymentMethods	0.0203	0.0202	0.00250	0.00261
	(0.0256)	(0.0256)	(0.00576)	(0.00576)
PaymentInstallments	0.00287	0.00282	−0.000851	−0.000843
	(0.00295)	(0.00296)	(0.000646)	(0.000646)
OrderItems	−0.315***	−0.318***	−0.0889***	−0.0893***
	(0.0200)	(0.0206)	(0.00512)	(0.00520)
RatingDelay	−0.0235***	−0.0234***	−0.00718***	−0.00717***
	(0.00609)	(0.00608)	(0.00154)	(0.00154)
DescriptionLength	0.0000274**	0.0000280**	4.84e-06*	5.03e-06*
	(0.0000106)	(0.0000106)	(2.23e-06)	(2.23e-06)
RepeatCustomer	0.258***	0.257***	0.0412***	0.0409***
	(0.0415)	(0.0415)	(0.00811)	(0.00811)
AverageCategoryScore	1.569***	1.563***	0.361***	0.360***
	(0.294)	(0.295)	(0.0675)	(0.0676)

(Continues)

TABLE 2 (Continued)

	Ordered logit model		Log-linear model	
	(1)	(2)	(3)	(4)
	Ratings	*Ratings*	*ln(Ratings)*	*ln(Ratings)*
SingleSeller	1.375***	1.362***	0.363***	0.360***
	(0.0847)	(0.0847)	(0.0245)	(0.0245)
SingleProduct	0.305***	0.301***	0.0980***	0.0972***
	(0.0577)	(0.0576)	(0.0153)	(0.0153)
Constant			−0.317	−0.315
			(0.287)	(0.280)
Time (month and year) dummies	Yes	Yes	Yes	Yes
Product category dummies	Yes	Yes	Yes	Yes
Customer location dummies	Yes	Yes	Yes	Yes
Payment type dummies	Yes	Yes	Yes	Yes
Observations	91,165	91,165	91,165	91,165
R^2			0.200	0.200

Note: Robust standard errors in parentheses.
$^{+}p < .1$; $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

promised delivery date. This possibility creates an endogeneity problem as the correlated unobservables may influence on-time performance but reside in the error term. More specifically, *EarlyDays* and *DelayDays* variables may be correlated with the error term ϵ_i in Equation (1). Given that the model in Equation (1) is non-linear, to address the endogeneity concern, we employ the control function approach following prior literature (Mallipeddi et al., 2021; Wu et al., 2021). In this approach, control variables, which are generated by instrument variables, are included in the main regression equation (i.e., Equation (1)). More specifically, the control functions are the residuals from the first stage regression wherein the instrument is used to explain the variation in the endogenous variable. Therefore, to generate control functions, we require instrument variables for the endogenous variables, that is, *EarlyDays* and *DelayDays*, that meet both the relevance criterion and the exclusion restriction (Angrist & Pischke, 2008). To satisfy the relevance criterion, the instrument should adequately explain the variation in the endogenous variable. The exclusion restriction criterion implies that the instrument is uncorrelated with the error term (ϵ_i) so that exogenous variation in the instrument affects the outcome of the main model (i.e., online rating) only through the endogenous variable.

In our context, it is plausible that a more established seller may have better delivery performance because of its operational capabilities (which we do not observe), whereas a seller with lower operational capabilities may generally have poor delivery performance. Hence, we use the seller's average delivery performance as an instrument for our endogenous variables. In particular, we postulate that the average delivery earliness of the seller, denoted by *AvgEarliness*, could explain variation of *EarlyDays*, that is, the number of days a delivery is made early. Similarly, the average lateness of the seller, represented by *AvgDelay*, could explain the variation in the number of days a delivery is delayed, that is, *DelayDays*. Hence, *AvgEarliness* and *AvgDelay* satisfy the relevance criterion. We also verify this in the first stage regression of the control function approach: *AvgEarliness* is positively associated with *EarlyDays* (with $p < .001$) and *AvgDelay* is positively associated with *DelayDays* (with $p < .001$). These instruments also satisfy the exclusion criterion as it is unlikely to be directly correlated with customer rating (i.e., the average earliness/delay score of the seller will not directly affect each customer's rating as the customer may not see the actual seller prior to delivery). Furthermore, our instruments are unlikely to be related to unobserved heterogeneity on the customer side.

Next, the delivery time may be endogenous as well. This is because we do not have granular data related to the shipping vendor firm. To address potential endogeneity in delivery time due to possible correlation with unobservables, we use an instrument variable to generate the control function for this endogenous variable. The distance between the seller and the customer (denoted by *Distance*) is likely to determine the time taken by the shipping vendor to deliver the package to the customer.

Hence, *Distance* satisfies the relevance criterion, which is verified by the first stage regression of the control function approach: *Distance* is positively correlated with *DeliveryTime* (with $p < .001$). In the context of this study, distance is unlikely to directly affect a customer's perception of the order, and therefore should only affect online ratings through delivery times.

The residuals from the first stage regression or the control functions (Δ_1, Δ_2, and Δ_3) are then included in the main model (i.e., Equation (1)) to alleviate the concerns of endogeneity. The parameter estimates of the model with control functions are provided in Table A2 in the Appendix. The results suggest that our main findings are robust against potential endogeneity, providing further support to the findings presented in Section 5. In particular, delivery time, order processing time, and late delivery of an order have negative and statistically significant effects on online ratings. In addition, we report a positive and statistically significant effect of early delivery on ratings. Furthermore, the direction of interaction effects are consistent with our main results.

6.2 | Alternative model specification

In Section 5, we reported the results using ordered logit and log-linear models. Given that the dependent variable in our study, *Rating*, is censored with a lower and upper bound, we follow the prior literature and supplement our main analysis with Tobit regression models (Ko et al., 2019) to verify the robustness of our results. The parameter estimates using the Tobit model are presented in Column 1 of Table A3 in the Appendix and are consistent with our earlier findings. Furthermore, we also check the robustness of our results using the linear model (i.e., without log-transforming the dependent variable). The estimates from the linear model are provided in Column 2 of Table A3. The estimates of this alternative models are consistent with our earlier findings.

6.3 | Alternative variable operationalization

While the key objective of this study is to understand the impact of absolute values of processing and delivery times on ratings, we extend our analyses to understand the effect of higher processing times relative to the delivery time on ratings. To do so, we first create a variable *ProcessDeliveryRatio*, which is operationalized by $\frac{ProcessingTime}{DeliveryTime}$. We now use this variable instead of the absolute measures of *ProcessingTime* and *DeliveryTime* in our main models (in Equation (1)). We find that the parameter estimate for the variable *ProcessDeliveryRatio* is negative and statistically significant. This indicates that higher processing times compared to the delivery times are associated with lower online ratings. These results are provided in Columns 1 (ordered logit model) and 2 (log-linear model) in Table A4 in the Appendix. This result speaks to our finding regarding Hypothesis 3 that the marginal impact of internal operational delays (i.e., processing time) is greater than external delays in the delivery process (i.e., delivery time).

In addition, we also extend our analysis to understand the impact of the ratios of the costs. Specifically, we generate a new variable, *OrderFreightRatio* (which is operationalized by $\frac{OrderValue}{FreightCost}$) and study the impact of this variable on online ratings. We find that the parameter estimate for the variable *OrderFreightRatio* negatively moderates the relationship between the number of days a delivery was delayed and ratings. However, we do not find evidence for a statistically significant effect of *OrderFreightRatio* on *EarlyDays*. These results suggest the presence of an asymmetric effect of *OrderFreightRatio* on online ratings. These results are provided in Columns 3 (ordered logit mode) and 4 (log-linear model) in Table A4 in the Appendix.

While one of our key objectives was to understand the differential impacts of order and freights costs, we extend our analysis to examine the effects of total cost of an order, where $TotalPrice = OrderValue + FreightCost$. More specifically, we examine the main effect of *TotalPrice* on online rating and the moderating effect of *TotalPrice* of an order on the relationship between positive and negative deviation from the promised delivery date and online rating. We estimate this alternative model using an ordered logit model. The results are presented in Column 1 of Table A5 in the Appendix. Similar to the results from the main model, we find that the processing time and delivery time have statistically significant negative effects on ratings and positive (negative) deviation from the promised delivery date has a positive (negative) effect on ratings. Next, the results indicate that the main effect of the total price on ratings is not statistically significant. However, we find that the total price may amplify the negative effect of *DelayDays* on *Rating*, which suggests that the total price may play a significant role on how customers evaluate delivery performance. We present the estimates of this log-linear model in Column 2 of Table A5.

6.4 | Relative ratings

As discussed earlier, we build our hypotheses on EDT, which posits that a customer's satisfaction is driven by her prior expectations. We conduct an additional robustness analysis to understand the effect of order fulfillment process on *relative* customer ratings. More specifically, variable $RelativeRating = Rating - AverageCategoryScore$

represents a customer's level of satisfaction, after accounting for any potential prior expectations regarding the purchased item(s). Hence, in addition to the control variables in our analyses, using *RelativeRating* as the dependent variable further rules out the influence of product category in affecting a customer's formation of her prior expectations about her shopping experience. The parameter estimates provided in Table A6 show that the results are consistent with those that are presented for the main model.

7 | POST-HOC ANALYSIS: CURVILINEAR IMPACT OF THE LENGTH OF DEVIATION

While our results demonstrate the positive and negative effects of delivery deviation (i.e., *DelayDays* and *EarlyDays*), prior research has argued that the relationship between time waiting for service and satisfaction may be curvilinear rather than linear (Giebelhausen et al., 2011). In the context of our study, waiting for service refers to waiting for the delivery of an order. The rationale behind the curvilinear effect of waiting and satisfaction originates in reference dependency theory, which posits that a customer's utility function is convex-shaped for losses and concave-shaped for gains (Bleichrodt et al., 2009). In our context, the negative effect of waiting for a delivery after the promised date follows a convex-shape curve, that is, it increases initially with the number of days the delivery is delayed and then starts to level off as the deviation increases further. Likewise, the positive effect of an early delivery is high when the deviation initially increases but gradually diminishes with an increasing positive deviation.

To empirically analyze this postulation, we add quadratic effects of *EarlyDays* and *DelayDays* to the model in Equation (1) and re-estimate the model. In Table A7 in the Appendix, we provide the parameter estimates of ordered logit (see Column 1), log-linear (see Column 2), and linear (see Column 3) models. The results indicate that the coefficients of both linear and quadratic terms are statistically significant. We illustrate the curvilinear relationship between *EarlyDays* and *Ratings* in Figure 4 and the curvilinear relationship between *DelayDays* and *Ratings* in Figure 5. We discuss the implications of these findings in Section 9.

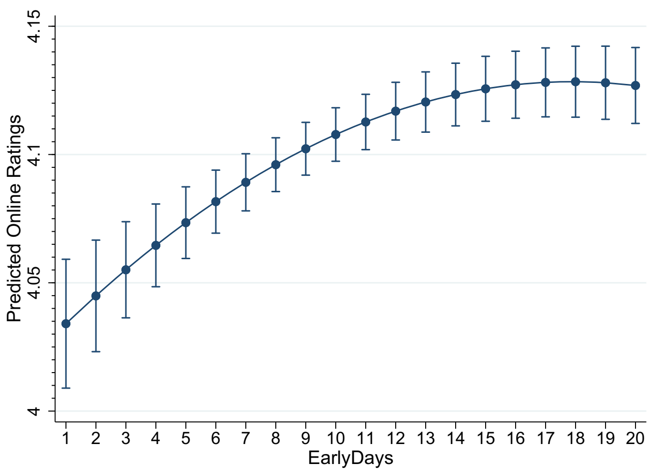

FIGURE 4 Curvilinear impact of *EarlyDays*

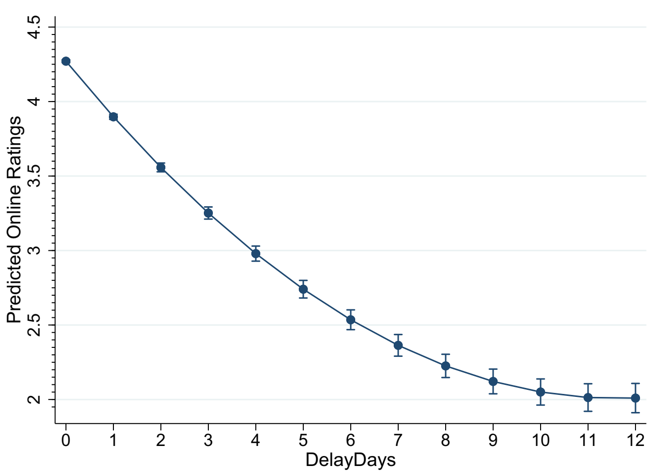

FIGURE 5 Curvilinear impact of *DelayDays*

8 | POST-HOC ANALYSIS: IMPACT OF TIMELINESS OF DELIVERY

Whereas the primary focus of this study is to investigate the effects of the length of deviation from the promised delivery date (i.e., the number of days an order is delivered late/early), we now extend our analyses to quantify the impact of the timeliness (either early or late) of an order on online ratings. In the context of our study, the order can be either late, early, or on-time. Therefore, we conduct the post-hoc analysis to answer the following questions: (1) What is the impact of order timeliness on online ratings? (2) Do order cost and freight cost moderate the relationship between late delivery and online ratings?

To answer these probing questions, we first operationalize the following variables—*Late* and *OnTime*. In particular, the variable *Late* captures whether the order was delivered after the promised delivery date. In particular, this variable represents the difference between the promised delivery date and the actual delivery date of an order such that $Late = 1$ if the order was delivered after the promised date, and $Late = 0$ otherwise. Similarly, variable $OnTime = 1$ when the order was delivered exactly on the promised delivery date and $OnTime = 0$ otherwise. Hence orders delivered early serve as the baseline group in our analysis.

We expect that late delivery of an order would, on average, have a negative effect on the ratings for an order. We found in our main analyses that order cost and freight cost may affect how a customer attributes the "responsibility" of late delivery between the online retailer and the shipping vendor. Similarly, we predict that order cost will intensify the negative effect of late delivery, whereas the freight cost will attenuate the negative impact of late delivery on ratings. We model the impact of late delivery on online rating for an order i using the ordered logit regression as follows:

$$\begin{aligned}\Pr(Rating_i = k) &= \Pr(\alpha_{k-1} < y_i^* < \alpha_k)\\ y_i^* &= \beta_0 + \beta_1 ProcessingTime_i + \beta_2 DeliveryTime_i + \beta_3 Late_i + \beta_4 OnTime_i\\ &\quad + \beta_5 OrderValue_i + \beta_6 FreightCost_i + \beta_7 Late_i \times OrderValue_i\\ &\quad + \beta_8 Late_i \times FreightCost_i + \mathbb{Z}\mathbb{C}_i + \epsilon_i,\end{aligned} \tag{2}$$

where β_1 and β_2 are the estimates of variables *ProcessingTime* and *DeliveryTime* respectively. Next, β_3 denotes the effect of late delivery on online ratings. Furthermore, the interaction terms *Late* × *OrderValue* and *Late* × *FreightCost* capture the moderating effects of order cost and freight cost on the relationship between *Late* and *Ratings*.

The parameter estimates of Equation (2) are presented in Column 1 of Table A8 in the Appendix. We find that the late delivery has a negative and statistically significant effect on online ratings. Next, we find that freight cost reduces the negative effect of late delivery while order cost further increases it. Our results continue to show that the processing and delivery times are negatively associated with online ratings. Furthermore, our results also show that the magnitude of β_1 is significantly larger than β_2, which suggests that the negative effect of *ProcessingTime* is larger than the negative effect of *DeliveryTime*.[6] To ensure the robustness of these results, we also estimate the same model using alternative estimation strategies. In particular, we use a log-linear model (See Column 2 in Table A8) and a Tobit model (See Column 3 in Table A8) to ensure robustness of our results. The results from these alternative models are substantively similar to the ordered logit model.

9 | DISCUSSION

Recent advances in various logistics technologies have enabled e-commerce firms to closely track shipments in the delivery process and obtain precise estimates of delivery times. Apart from improving efficiency and reducing uncertainties in operations, these technologies also provide firms with the option to make such information available to their customers to allow better visibility into the order fulfillment process. This allows customers to observe a firm's order fulfillment performance before their orders are delivered. It is therefore critical to understand how such information, in addition to the actual delivery time, potentially affects customers' evaluation of their online shopping experience, especially in the form of online customer ratings.

Using a unique data set obtained from an e-commerce firm from a developing economy, we find that longer order processing time and delivery time are associated with decreased online ratings. This relationship holds regardless of the actual delivery status (i.e., late, early, or on-time) of an order. In addition, our results suggest that the negative impact of order processing time is larger than that of delivery time. Next, we demonstrate that late delivery (measured by the number of days an order is delivered late) has a negative and significant effect on online ratings whereas early delivery (measured by the number of days an order is delivered early) is positively associated with online ratings. Furthermore, our results suggest that the relationship between the timeliness of the delivery and online ratings is moderated by how customers attribute responsibilities between the firm and the third-party shipping vendor. In particular, we find that the negative marginal impact of late delivery is larger when the order cost is higher and freight cost is lower. Furthermore, the positive impact of early delivery is attenuated by higher freight cost.

9.1 | Theoretical implications

Prior research on the effects of order fulfillment performance on customer satisfaction typically assumes that satisfaction is driven by the final delivery status alone because information regarding the order fulfillment process before the actual delivery is not readily accessible to customers (e.g., Zhang et al., 2019). The advances in logistics tracking technologies reduce such an information asymmetry and allow customers to observe the performance of order fulfillment processes before receiving the delivery. Our study, to the best of our knowledge, is the first to quantify the relationship between the *observed* order fulfillment times prior to the delivery and customer satisfaction in the form of online ratings. Through the theoretical lens of EDT, we argue that observing performance information regarding the order fulfillment process creates additional opportunities for customers to evaluate the progress of the fulfillment process against their prior expectations. As a result, disconfirmation of expectations, and hence dissatisfaction, may occur even before a customer observes the actual delivery time. Thus, our study adopts an expectation-disconfirmation perspective and contributes to the theoretical understanding of the effects of order fulfillment processes prior to delivery on online ratings.

Recent studies suggest that allowing customers to observe a firm's operations may lead to better perceived performance compared to situations where visibility is not provided (e.g., Buell et al., 2017). Diverging from these studies, we examine how information regarding a firm's internal operations may affect perceived performance, given that the firm decided to make their operations visible to customers. We find strong evidence that information that tracks the firm's order fulfillment processes may affect a customer's level of satisfaction, potentially in a negative manner. Therefore, the observed order fulfillment process before actual delivery becomes a salient part of an online customer's perceived experience due to his/her visibility into the processes. This result can be explained by EDT, which suggests that customers actively evaluate their experience throughout a service encounter instead of relying solely on the final outcomes (e.g., Coye, 2004; Rust et al., 1999). Negative disconfirmation and dissatisfaction may therefore occur if a firm's internal order fulfillment process does not meet a customer's prior expectations. Subsequently, our study contributes to this stream of literature by highlighting the importance of clearly identifying what parts of operations are visible to customers when investigating customer satisfaction using EDT.

Prior research argues that the outcome of the order fulfillment process (i.e., the timeliness of the delivery) impacts customer satisfaction (Zeithaml, 2000). However, these studies typically focus only on late deliveries, with Peng and Lu (2017) being an exception in a B2B context. In a B2C setting, however, our study is perhaps the first to examine the effects of both early delivery and late delivery on online customer satisfaction simultaneously. Furthermore, most of the previous studies have investigated the effects of late delivery in the context of a developed economy. Our results conform to the extant literature that reports a negative relationship between late delivery and customer satisfaction. Thus, our study provides evidence that the negative impacts of late delivery can be generalized to a global setting. In addition, we further demonstrate that early delivery is positively associated with customer satisfaction. As such, we fill the gap in the extant literature, which has not examined the effect of early delivery in online retailing contexts.

Our work also complements the theoretical predictions in Peng and Lu (2017), who conceptualize that B2B customers evaluate order fulfillment performance in terms of the accuracy of delivery time (i.e., order delivery precisely at the scheduled time). They find some evidence that early delivery in B2B contexts is viewed negatively by customer firms because it is a violation of accurate delivery time. In contrast, we show that online retail customers may be less sensitive to the accuracy of delivery time if the delivery is made earlier than the promised delivery date. Thus, early delivery is generally considered desirable in online retailing contexts.

Using the granular information contained in our data set, we explicitly examine the magnitudes of both positive and negative deviations from the promised delivery date. We find that, as the number of days an order is delivered late (early) increases, the online customer rating decreases (increases). Moreover, as depicted in Figures 4 and 5, the marginal increase or decrease in online ratings becomes largely negligible after an order is early by about 14 days or late by 7 days. The diminishing impacts of late delivery and early delivery suggest that online customers form their level of satisfaction of the delivery time based more on *whether* their orders are delivered on time, compared to *for how long* the orders are delivered late/early. Our post-hoc analysis in Section 8 further corroborates this finding. Consequently, online retailers should carefully evaluate the benefit of expediting their fulfillment process to achieve early delivery because the associated benefit may not always outweigh the costs. More importantly, firms should be cautious about setting a definite promised delivery date, especially when meeting the promised date is challenging for their order fulfillment process. A slight delay compared to a clearly stated promised delivery date may immediately have a strongly negative impact on customer satisfaction (Ofir & Simonson, 2007).

Furthermore, we find that the effects of late delivery and early delivery are asymmetric. In particular, our results suggest that the negative impact of late delivery on online ratings is stronger than the positive impact of early delivery. This finding speaks to the extant research on reference dependency theory, which posits that a positive deviation (i.e., early delivery in our study) and a negative deviation (i.e., late delivery) are associated with two distinctive situations, namely a gain or a loss with respect to an individual's reference point (Tereyağoğlu et al., 2018). Our result is consistent with this theoretical prediction such that online customers use the estimated delivery time as a salient reference point in evaluating the order fulfillment process. It seems that online customers exhibit loss aversion in evaluating an online retailer's order fulfillment process such that they are more sensitive towards late delivery than early delivery. Our robustness analysis reveals that this result also holds when accounting for the potential influence of product category in affecting a customer's formation of prior expectations. Overall, resting on the rich information contained in our data set, our study is the first to illustrate that online customers exhibit reference dependence in evaluating online retailers' order fulfillment performance.

9.2 | Managerial implications

Our results yield several important managerial implications. First and foremost, the implementation of Industry 4.0 technologies such as IoT and artificial intelligence has been shown to significantly enhance retailers' order fulfillment capabilities in various settings (Digiteum, 2021). Yet, how the impact of these technological advancements may reach beyond firms' internal operations remains largely unexplored. Our study suggests that these technologies may influence online customers as well, particularly in terms of how they evaluate their shopping experience. The detailed and up-to-date information supplied by the logistics tracking technologies enables customers to promptly evaluate a retailer's order fulfillment process even before the actual delivery is completed. Thus, retailers should recognize that information regarding their order fulfillment processes before the delivery may result in lowered online customer ratings. Hence, e-commerce firms need to be careful in utilizing logistics tracking technologies to provide timely delivery information to customers because doing so may expose potential inefficiencies or failures in their order fulfillment processes, which in turn may lead to customer dissatisfaction. Such a relationship holds regardless of if an order is eventually delivered on-time or even earlier than the promised time. Our results are indicative that online retailers should recognize that their previously internal operations can become an important factor in driving customer satisfaction if they provide customers with visibility into these operations.

In addition, the use of various logistics tracking technologies has improved the accuracy of estimated delivery time. However, online retailers may need to be cautious in sharing these estimates with customers because even a one-day deviation from the promised delivery time may impact online ratings significantly. On the one hand, our results show that the negative impact of late delivery is generally higher than the positive impact of early delivery. Thus, online retailers should focus more on eliminating delayed orders than on expediting orders that can already be delivered at or before the promised delivery time. On the other hand, the marginal impact of late delivery is the highest immediately after an order is delayed. Thus, even a slight delay of delivery has a significantly negative impact on online ratings. In contrast, the incremental benefit of delivering an order much earlier than promised time may be limited. Thus, provided that an online retailer can consistently sustain on-time deliveries, the benefit of early delivery in terms of improving online customer ratings may not always justify the extra costs required to expedite the order fulfillment process. Taken together, our study suggests that online retailers should strive to deliver customer orders on-time or slightly early, but avoid any late delivery whenever possible. In this sense, online retailers may be better off providing a relatively longer estimated delivery time to customers so that the likelihood of customers observing late delivery is minimized.

Our results suggest that customers' online ratings are affected more severely when observed inefficiencies are located in a retailer's internal operations (i.e., long order processing time), as opposed to in a third-party vendor (i.e., long delivery time). Thus, retailers should clearly announce their use of third-party shipping services to customers and focus on coordinating with the sellers and their logistics partners so that orders are processed promptly. Retailers should also invest in technologies and managerial practices to improve their internal operations in terms of inventory and warehousing management capabilities so that order processing time can be reduced in general.

Furthermore, our results suggest that a retailer's pricing strategy may also affect how customers react to delays in order delivery. Our results suggest that online customer ratings are generally less affected by late deliveries for orders that have lower order costs and higher freight costs. As such, it may be beneficial for a retailer to clearly list shipping cost as a separate charge to customers, rather than simply providing the total cost of orders. The retailer may also safeguard against the impact of late deliveries by lowering the list prices of merchandise but charging higher shipping fees. It may also achieve this goal indirectly by increasing the threshold order value beyond which free shipping is provided. Nevertheless, these strategies may be less desirable in the event of early delivery because they may attenuate the positive relationship between early delivery and customer satisfaction.

Our findings also suggest that e-commerce firms need to take into account important trade-offs when making granular information available to the customers. Our results show that the negative impact of poor order fulfillment performance on customer satisfaction is higher when the retailer should be held accountable rather than the third-party shipping vendor. Therefore, in situations where the cause of poor order fulfillment performance is external to the retailer, its negative impact on customer satisfaction may be mitigated since customers can clearly distinguish a retailer's internal operations and hence its responsibilities from those of the external shipping vendor based on the detailed information furnished through logistics tracking technologies. Nevertheless, a retailer that is unable to maintain an efficient order processing operation internally may be punished more severely because any delays or failures will be exposed to customers completely.

Finally, customer ratings have become critical for e-commerce firms as customers are increasingly engaging in online purchases. Our findings suggest that customers may react to subpar order fulfillment performance and voice their dissatisfaction in the form of lower online customer ratings, even when an external logistics partner (rather than the retailer itself) should be held responsible. Furthermore, customers may not apportion blame between a retailer and its logistics partner appropriately when observing dissatisfactory order fulfillment performance if the presence of the logistics partner is not recognized. Therefore, e-commerce firms may consider allowing separate ratings for products and delivery performance. In doing so, poor order fulfillment performance caused by external parties may be less reflected in the overall online ratings. Thus, the negative impact of order fulfillment inefficiencies on customer's future purchase decisions may be attenuated.

9.3 | Limitations and directions for future research

Our research findings point out several directions for future study. First, future research may explore additional moderating factors that influence the relationship between the order fulfillment process and customer satisfaction, especially in the form of online ratings. Our study demonstrates that various aspects in the fulfillment process (i.e., internal order processing, external delivery, and actual delivery time) have distinctive and independent effects on customer satisfaction. It is therefore possible that each of the effects will be moderated by different sets of factors. Second, future research can potentially explore if the various aspects of the fulfillment process may have differential effects on customers' future decisions in the long term. For instance, it is possible that inefficiencies in a retailer's internal order processing operations may have a stronger effect in a customer's future purchase decisions, compared to previous delays caused by a third-party shipping vendor during order delivery. Other factors regarding the order fulfillment process such as whether the order package is delivered to a safe and convenient location designated by online customers may also impact customer satisfaction. Such factors may also interact with total cost of purchase and pricing structure in jointly affecting online customer's purchase decision. Third, future studies may further examine how e-commerce firms can systematically manage the timeliness of order fulfillment related information disclosed to customers during an online purchase. Finally, our study relies on secondary data that only allows us to examine the relationship between the order fulfillment process and online ratings given that relevant fulfillment information is provided to online customers. Future studies can seek to cross-validate our findings in other empirical contexts. Moreover, other empirical methodologies including field experiments may be conducted to examine whether such information should be provided to customers at all. Case studies or experimental methodologies can also be employed to determine which information disclosure policy(ies) will generally lead to desirable outcomes.

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ENDNOTES

[1] In our data, 188 observations (out of 93,131) reported multiple ratings for an order. For the main analysis, we have used the highest rating of the multiple ratings. For robustness, we have re-run the empirical model using the average of the multiple ratings. Our results do not change and are qualitatively similar.

[2] We thank the review team for this excellent suggestion to control for average ratings for each product category.

[3] A negative *RatingDelay* indicates that the ratings was left prior to the delivery of the order.

[4] Winsorizing data at 99% leaves us with 91,165 observations.

[5] The null hypothesis, H_0: $\beta_3 = \beta_4$ is rejected with p-value <.001.

[6] The null hypothesis, H_0: $\beta_1 = \beta_2$ is rejected with p-value <.001.

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How to cite this article: Akturk, M. S., Mallipeddi, R. R., & Jia, X. (2022). Estimating impacts of logistics processes on online customer ratings: Consequences of providing technology-enabled order tracking data to customers. *Journal of Operations Management*, *68*(6-7), 775–811. https://doi.org/10.1002/joom.1204

APPENDIX

ESTIMATING THE IMPACT OF LOGISTICS PROCESSES ON ONLINE CUSTOMER RATINGS

Tables—Summary statistics

TABLE A1 Summary statistics for variables

Variables	Description	Mean	SD	Min	Max
Control variables					
*CategoryD*1 (Binary)	=1 if product belong to Auto and Industrial category, else 0	0.08	0.28	0	1
*CategoryD*2 (Binary)	=1 if product belong to Books category, else 0	0.010	0.10	0	1
*CategoryD*3 (Binary)	=1 if product belong to Electronics category, else 0	0.24	0.43	0	1
*CategoryD*4 (Binary)	=1 if product belong to Fashion category, else 0	0.076	0.27	0	1
*CategoryD*5 (Binary)	=1 if product belong to Home Goods category, else 0	0.46	.50	0	1
*CategoryD*6 (Binary)	=1 if product belong to Office category, else 0	0.065	0.25	0	1
PaymentVoucher (Binary)	=1 if payment made by voucher, else 0	0.038	0.19	0	1
PaymentCredit (Binary)	=1 if payment made by credit, else 0	0.77	0.42	0	1
PaymentDebit (Binary)	=1 if payment made by debit, else 0	0.15	0.12	0	1
PaymentBoleto (Binary)	=1 if payment made by boleto, else 0	0.19	0.39	0	1

Note: For brevity, we do not report the summary statistics for the baseline Dummy variables. We control for 27 *CustomerLocation* fixed effects using dummy variables. We control for time fixed effects using dummy variables for month and year.

Tables—Robustness checks

TABLE A2 Robustness check—Accounting for endogeneity

Ordered logit	(1) Ratings
ProcessingTime	−0.0476***
	(0.00426)
DeliveryTime	−0.0453***
	(0.00577)
DelayDays	−0.475***
	(0.0912)
EarlyDays	0.0193***
	(0.00401)
EarlyDays × OrderValue	0.00000269
	(0.00000617)
EarlyDays × FreightCost	−0.000182**
	(0.0000595)
DelayDays × OrderValue	−0.000123***
	(0.0000361)
DelayDays × FreightCost	0.000801+
	(0.000425)
OrderValue	0.0000648
	(0.0000921)
FreightCost	0.00223*
	(0.00106)
Weight	−0.00000651*
	(0.00000329)
Volume	0.000000446
	(0.000000519)
Photos	−0.00802*
	(0.00392)
PaymentMethods	0.0215
	(0.0256)
PaymentInstallments	0.00229
	(0.00298)
OrderItems	−0.314***
	(0.0214)
RatingDelay	−0.182**
	(0.0635)
DescriptionLength	0.0000267*
	(0.0000107)
RepeatCustomer	0.243***
	(0.0418)
AverageCategoryScore	1.572***
	(0.298)
SingleSeller	1.391***
	(0.0853)
SingleProduct	0.302***
	(0.0576)
Control function for *EarlyDays*, Δ_1	−0.00761
	(0.00395)
Control function for *DelayDays*, Δ_2	0.228*
	(0.0905)
Control function for *Delivery*, Δ_3	−0.00472
	(0.00613)
Time (month and year) dummies	Yes
Product category dummies	Yes
Customer location dummies	Yes
Payment type dummies	Yes
Observations	91,165

Note: Robust standard errors in parentheses.
$^+p < .1$; $^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE A3 Robustness checks—Tobit regression model and linear model

	Tobit model	Linear model
	(1)	(2)
	Rating	***Rating***
ProcessingTime	−0.104***	−0.0362***
	(0.00401)	(0.00146)
DeliveryTime	−0.0830***	−0.0278***
	(0.00285)	(0.000985)
DelayDays	−0.418***	−0.187***
	(0.0186)	(0.00607)
EarlyDays	0.0221***	0.00775***
	(0.00305)	(0.00102)
EarlyDays × OrderValue	0.00000289	0.000000908
	(0.0000105)	(0.00000350)
EarlyDays × FreightCost	−0.000310**	−0.0000922*
	(0.0000995)	(0.0000373)
DelayDays × OrderValue	−0.000179**	−0.0000317**
	(0.0000551)	(0.0000111)
DelayDays × FreightCost	0.00123*	0.000448*
	(0.000585)	(0.000185)
OrderValue	0.0000590	−0.00000256
	(0.000151)	(0.0000519)
FreightCost	0.00442**	0.00121
	(0.00170)	(0.000647)
Weight	−0.0000101	−0.00000227
	(0.00000573)	(0.00000196)
Volume	0.000000448	4.61e-08
	(0.000000906)	(0.000000308)
Photos	−0.0124	−0.00171
	(0.00680)	(0.00220)
PaymentMethods	0.0296	0.00979
	(0.0450)	(0.0149)
PaymentInstallments	0.00291	−0.00118
	(0.00517)	(0.00171)
OrderItems	−0.583***	−0.227***
	(0.0350)	(0.0132)
RatingDelay	−0.0451***	−0.0189***
	(0.0103)	(0.00390)
DescriptionLength	0.0000473*	0.0000161**
	(0.0000186)	(0.00000595)
RepeatCustomer	0.440***	0.123***
	(0.0715)	(0.0218)
AverageCategoryScore	2.748***	0.982***
	(0.509)	(0.176)
SingleSeller	2.165***	0.962***
	(0.142)	(0.0608)
SingleProduct	0.573***	0.241***
	(0.0980)	(0.0388)
Constant	−6.380**	−0.338
	(2.106)	(0.727)
Time (month and year) dummies	Yes	Yes
Product category dummies	Yes	Yes
Customer location dummies	Yes	Yes
Payment type dummies	Yes	Yes
Observations	91,165	91,165
R^2		0.184

(Continues)

TABLE A3 (Continued)

Note: Robust standard errors in parentheses.
$^*p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE A4 Robustness checks—Alternative variable operationalization

	Ordered logit	Log-linear	Ordered logit	Log-linear
	(1)	(2)	(3)	(4)
	Rating	ln(*Rating*)	*Rating*	ln(*Rating*)
ProcessDeliveryRatio	−0.0326***	−0.00760***	−0.0327***	−0.00746***
	(0.00503)	(0.00126)	(0.00501)	(0.00125)
DelayDays	−0.326***	−0.0942***	−0.293***	−0.0880***
	(0.0125)	(0.00234)	(0.00993)	(0.00199)
EarlyDays	0.0327***	0.00615***	0.0299***	0.00589***
	(0.00175)	(0.000386)	(0.00155)	(0.000327)
EarlyDays × OrderValue	−0.000000522	−0.000000391		
	(0.00000669)	(0.00000143)		
EarlyDays × FreightCost	−0.0000975	−0.0000106		
	(0.0000609)	(0.0000151)		
DelayDays × OrderValue	−0.000147***	−0.0000165***		
	(0.0000403)	(0.00000480)		
DelayDays × FreightCost	0.00105*	0.000213**		
	(0.000418)	(0.0000688)		
EarlyDays × OrderFreightRatio			0.0000117	−0.0000185
			(0.000177)	(0.0000355)
DelayDays × OrderFreightRatio			−0.00461***	−0.000515***
			(0.00113)	(0.000149)
OrderFreightRatio			0.00685**	0.000693
			(0.00235)	(0.000491)
OrderValue	0.000131	0.00000296		
	(0.000102)	(0.0000212)		
FreightCost	−0.00122	−0.000349		
	(0.00100)	(0.000261)		
Weight	−0.00000749*	−0.000000748	−0.0000105***	−0.00000154*
	(0.00000330)	(0.000000769)	(0.00000306)	(0.000000707)
Volume	0.000000599	1.92e-08	0.000000264	−6.60e-08
	(0.000000517)	(0.000000120)	(0.000000496)	(0.000000114)
Photos	0.000867	0.00182*	0.000911	0.00180*
	(0.00387)	(0.000815)	(0.00388)	(0.000816)
PaymentMethods	0.0166	0.00189	0.0166	0.00166
	(0.0250)	(0.00572)	(0.0251)	(0.00574)
PaymentInstallments	−0.00190	−0.00174**	−0.00546	−0.00224***
	(0.00296)	(0.000651)	(0.00297)	(0.000657)
OrderItems	−0.266***	−0.0811***	−0.293***	−0.0879***
	(0.0208)	(0.00536)	(0.0171)	(0.00454)
RatingDelay	−0.0192***	−0.00638***	−0.0194***	−0.00645***
	(0.00577)	(0.00152)	(0.00579)	(0.00152)
DescriptionLength	0.0000361***	0.00000665**	0.0000284**	0.00000518*
	(0.0000106)	(0.00000224)	(0.0000105)	(0.00000223)

TABLE A4 (Continued)

	Ordered logit	Log-linear	Ordered logit	Log-linear
	(1)	(2)	(3)	(4)
	Rating	ln(*Rating*)	*Rating*	ln(*Rating*)
RepeatCustomer	0.239***	0.0381***	0.242***	0.0383***
	(0.0414)	(0.00817)	(0.0414)	(0.00819)
AverageCategoryScore	1.612***	0.376***	1.593***	0.375***
	(0.287)	(0.0673)	(0.286)	(0.0673)
SingleSeller	1.348***	0.359***	1.354***	0.360***
	(0.0840)	(0.0246)	(0.0839)	(0.0246)
SingleProduct	0.289***	0.0958***	0.288***	0.0960***
	(0.0574)	(0.0154)	(0.0575)	(0.0154)
Constant		−0.585*		−0.584*
		(0.279)		(0.278)
Time (month and year) dummies	Yes	Yes	Yes	Yes
Product category dummies	Yes	Yes	Yes	Yes
Customer location dummies	Yes	Yes	Yes	Yes
Payment type dummies	Yes	Yes	Yes	Yes
Observations	90,885	90,885	90,566	90,566
R^2		0.191		0.190

Note: Robust standard errors in parentheses.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE A5 Robustness checks—Total price

	Ordered logit (1) *Rating*	Log-linear (2) ln(*Rating*)
ProcessingTime	−0.0599***	−0.0128***
	(0.00229)	(0.000574)
DeliveryTime	−0.0485***	−0.00920***
	(0.00160)	(0.000371)
DelayDays	−0.234***	−0.0760***
	(0.00918)	(0.00196)
EarlyDays	0.0100***	0.00211***
	(0.00151)	(0.000318)
EarlyDays × TotalPrice	−0.00000578	−0.00000130
	(0.00000534)	(0.00000119)
DelayDays × TotalPrice	−0.0000674*	−0.00000524
	(0.0000279)	(0.00000395)
TotalPrice	0.000151	0.00000668
	(0.0000844)	(0.0000182)
Weight	−0.00000600	−0.000000339
	(0.00000313)	(0.000000711)
Volume	0.000000573	3.35e-08
	(0.000000504)	(0.000000114)
Photos	−0.00874*	−0.0000313
	(0.00389)	(0.000812)
PaymentMethods	0.0204	0.00253
	(0.0256)	(0.00576)
PaymentInstallments	0.00276	−0.000853
	(0.00297)	(0.000647)
OrderItems	−0.310***	−0.0877***
	(0.0176)	(0.00457)
RatingDelay	−0.0235***	−0.00719***
	(0.00609)	(0.00154)
DescriptionLength	0.0000276**	0.00000490*
	(0.0000106)	(0.00000223)
RepeatCustomer	0.258***	0.0411***
	(0.0415)	(0.00811)
AverageCategoryScore	1.571***	0.361***
	(0.294)	(0.0675)
SingleSeller	1.374***	0.363***
	(0.0847)	(0.0245)
SingleProduct	0.305***	0.0980***
	(0.0576)	(0.0153)
Constant		−0.320
		(0.279)
Time (month and year) dummies	Yes	Yes
Product category dummies	Yes	Yes
Customer location dummies	Yes	Yes
Payment type dummies	Yes	Yes
Observations	91,165	91,165
R^2		0.200

Note: Robust standard errors in parentheses.
*$p < .05$; **$p < .01$; ***$p < .001$.

TABLE A6 Robustness check—Relative ratings

	Linear model
	(1)
	RelativeRating
ProcessingTime	−0.0362***
	(0.00146)
DeliveryTime	−0.0278***
	(0.000986)
DelayDays	−0.187***
	(0.00607)
EarlyDays	0.00775***
	(0.00102)
EarlyDays × OrderValue	0.000000909
	(0.00000350)
EarlyDays × FreightValue	−0.0000922*
	(0.0000373)
DelayDays × OrderValue	−0.0000317**
	(0.0000111)
DelayDays × FreightValue	0.000448*
	(0.000185)
OrderValue	−0.00000259
	(0.0000519)
FreightValue	0.00121
	(0.000647)
Weight	−0.00000227
	(0.00000196)
Volume	4.60e-08
	(0.000000308)
Photos	−0.00171
	(0.00219)
PaymentMethods	0.00979
	(0.0150)
PaymentInstallments	−0.00118
	(0.00171)
OrderItems	−0.227***
	(0.0132)
RatingDelay	−0.0189***
	(0.00390)
DescriptionLength	0.0000162**
	(0.00000595)
RepeatCustomer	0.123***
	(0.0218)
SingleSeller	0.962***
	(0.0608)
SingleProduct	0.241***
	(0.0388)
Constant	−0.412***
	(0.104)
Observations	91,165
R^2	0.182
F	193.9

Note: Robust standard errors in parentheses.
*$p < .05$; **$p < .01$; ***$p < .001$.

TABLE A7 Post-hoc analysis: The curvilinear effect of deviation

	Ordered logit	Log-linear	Linear
	(1)	(2)	(3)
	Rating	ln (*Rating*)	*Rating*
ProcessingTime	−0.0547***	−0.0109***	−0.0316***
	(0.00230)	(0.000569)	(0.00145)
DeliveryTime	−0.0444***	−0.00766***	−0.0235***
	(0.00167)	(0.000382)	(0.000998)
DelayDays	−0.489***	−0.166***	−0.394***
	(0.0142)	(0.00369)	(0.00880)
DelayDays × DelayDays	0.0215***	0.00702***	0.0168***
	(0.000827)	(0.000233)	(0.000534)
EarlyDays	0.0231***	0.00385***	0.0138***
	(0.00375)	(0.000836)	(0.00223)
EarlyDays × EarlyDays	−0.000502***	−0.0000923***	−0.000331***
	(0.000120)	(0.0000261)	(0.0000701)
EarlyDays × OrderValue	0.00000385	−0.000000217	2.41e-08
	(0.00000598)	(0.00000136)	(0.00000347)
EarlyDays × FreightCost	−0.000177**	−0.0000313*	−0.0000888*
	(0.0000589)	(0.0000146)	(0.0000373)
DelayDays × OrderValue	−0.0000823***	−0.0000147***	−0.0000323***
	(0.0000229)	(0.00000359)	(0.00000864)
DelayDays × FreightCost	0.000483	0.000130*	0.000357*
	(0.000285)	(0.0000591)	(0.000149)
OrderValue	0.0000374	−0.00000178	0.0000144
	(0.0000900)	(0.0000202)	(0.0000520)
FreightCost	0.00251*	0.000382	0.00109
	(0.00103)	(0.000255)	(0.000647)
Weight	−0.00000708*	−0.000000608	−0.00000247
	(0.00000327)	(0.000000733)	(0.00000193)
Volume	0.000000428	1.84e-08	9.11e-08
	(0.000000515)	(0.000000116)	(0.000000305)
Photos	−0.00806*	0.000139	−0.00133
	(0.00390)	(0.000806)	(0.00218)
PaymentMethods	0.0178	0.00156	0.00716
	(0.0254)	(0.00570)	(0.0148)
PaymentInstallments	0.00233	−0.00101	−0.00163
	(0.00296)	(0.000641)	(0.00170)
OrderItems	−0.318***	−0.0892***	−0.226***
	(0.0207)	(0.00520)	(0.0133)
RatingDelay	−0.0101	−0.00222	−0.00687
	(0.00575)	(0.00144)	(0.00367)
DescriptionLength	0.0000293**	0.00000544*	0.0000171**
	(0.0000106)	(0.00000221)	(0.00000590)

TABLE A7 (Continued)

	Ordered logit	Log-linear	Linear
	(1)	(2)	(3)
	Rating	ln(***Rating***)	***Rating***
RepeatCustomer	0.263***	0.0420***	0.126***
	(0.0417)	(0.00804)	(0.0216)
AverageCategoryScore	1.439***	0.334***	0.901***
	(0.292)	(0.0671)	(0.174)
SingleSeller	1.368***	0.358***	0.957***
	(0.0851)	(0.0245)	(0.0607)
SingleProduct	0.297***	0.0959***	0.238***
	(0.0578)	(0.0152)	(0.0386)
Constant		−0.213	−0.0372
		(0.278)	(0.721)
Time (month and year) dummies	Yes	Yes	Yes
Product category dummies	Yes	Yes	Yes
Customer location dummies	Yes	Yes	Yes
Payment type dummies	Yes	Yes	Yes
Observations	91,165	91,165	91,165
R^2		0.216	0.198

Note: Robust standard errors in parentheses.
$^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE A8 Post-hoc analysis: Impact of delivery timeliness

	Ordered logit	Log-linear	Tobit
	(1)	(2)	(3)
	Rating	ln(*Rating*)	*Rating*
ProcessingTime	−0.0590***	−0.0120***	−0.103***
	(0.00213)	(0.000545)	(0.00381)
DeliveryTime	−0.0477***	−0.00840***	−0.0796***
	(0.00145)	(0.000343)	(0.00256)
OnTime	−0.0754	−0.00730	−0.112
	(0.0537)	(0.0132)	(0.0946)
Late	−1.844***	−0.640***	−3.411***
	(0.0604)	(0.0152)	(0.0947)
Late × OrderValue	−0.000519***	−0.000114**	−0.000835**
	(0.000142)	(0.0000353)	(0.000258)
Late × FreightCost	0.00463**	0.00102*	0.00835**
	(0.00169)	(0.000433)	(0.00283)
OrderValue	0.0000859	−0.00000348	0.000103
	(0.0000444)	(0.00000946)	(0.0000750)
FreightCost	0.000239	−0.0000280	0.000279
	(0.000567)	(0.000142)	(0.000969)
Weight	−0.00000732*	−0.000000746	−0.0000120*
	(0.00000321)	(0.000000743)	(0.00000570)
Volume	0.000000529	5.12e-08	0.000000810
	(0.000000510)	(0.000000118)	(0.000000906)
Photos	−0.00925*	−0.000100	−0.0134*
	(0.00384)	(0.000811)	(0.00679)
PaymentMethods	0.0199	0.00160	0.0236
	(0.0249)	(0.00563)	(0.0441)
PaymentInstallments	0.00241	−0.00108	0.00184
	(0.00291)	(0.000642)	(0.00514)
OrderItems	−0.317***	−0.0887***	−0.584***
	(0.0198)	(0.00512)	(0.0344)
RatingDelay	−0.0163**	−0.00266**	−0.0445***
	(0.00496)	(0.000830)	(0.00588)
DescriptionLength	0.0000281**	0.00000491*	0.0000469*
	(0.0000105)	(0.00000222)	(0.0000186)
RepeatCustomer	0.269***	0.0447***	0.464***
	(0.0411)	(0.00803)	(0.0712)
AverageCategoryScore	1.271***	0.311***	2.327***
	(0.268)	(0.0615)	(0.463)
SingleSeller	1.389***	0.371***	2.242***
	(0.0832)	(0.0242)	(0.141)
SingleProduct	0.273***	0.0888***	0.519***
	(0.0569)	(0.0151)	(0.0981)

TABLE A8 (Continued)

	Ordered logit	Log-linear	Tobit
	(1)	**(2)**	**(3)**
	Rating	$\ln(\boldsymbol{Rating})$	***Rating***
Constant		−0.0911	−4.360*
		(0.255)	(1.920)
Time (month and year) dummies	Yes	Yes	Yes
Product category dummies	Yes	Yes	Yes
Customer location dummies	Yes	Yes	Yes
Payment type dummies	Yes	Yes	Yes
Observations	93,131	93,131	93,131
R^2		0.220	

Note: Robust standard errors in parentheses.
*$p < .05$; **$p < .01$; ***$p < .001$.