Proceedings of the 2024 Winter Simulation Conference
H. Lam, E. Azar, D. Batur, S. Gao, W. Xie, S. R. Hunter, and M. D. Rossetti, eds.

ORDER LEAD TIME INFLUENCING FACTORS IN THE SEMICONDUCTOR SUPPLY CHAIN

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ABSTRACT

Determining and communicating reliable order lead time information is vital to retain customers and increase supply chain resilience, especially in complex settings such as the semiconductor supply chain. To overcome shortcomings of recent research on order lead time and its influencing factors, we collect order data from a global semiconductor manufacturer that captures both make-to-plan and make-to-order information within the internal supply chain. Our contribution is twofold. First, our results support an accurate prediction of the confirmed order lead time and thus its reliable communication to customers. We develop three linear regression models: one general, one conventional, and one model for particular situations where standard delivery times are hard to determine. Second, we develop three specific managerial implications by analyzing influencing factors that highly correlate with the confirmed order lead time and capture information on the customer request, order fulfillment details, and product specifics.

1 INTRODUCTION

In an era of digital technology, semiconductors have become the critical components underpinning the ongoing digital path. The resilience of the semiconductor industry is exemplified by its robust growth trajectory, even in the face of global disruptions such as the COVID-19 pandemic. This growth is due to an increasing demand for semiconductors, pivotal to various digital devices, functioning as memory controllers, microprocessors, and power management systems. The production of semiconductors is demanding and characterized by intricate circuit designs and an extensive manufacturing process encompassing up to a thousand processing steps (Ehm and Lachner 2019). This complexity is compounded by several industry-specific challenges, including a volatile market, short product life cycles, and rapid technological innovation. These factors contribute to significant variability within the semiconductor supply chain, manifesting in demand and Order Lead Time (OLT) fluctuations (Li et al. 2019). OLT, according to Gunasekaran et al. (2001), "refers to the time which elapses between the receipt of the customer's order and the delivery of the goods" (p. 73). Following the definition of Li et al. (2015), in this study we define Confirmed Order Lead Time (OLTc) as "the time between the receiving of an order and the promised due date" (p. 362).

This study investigates OLTc and its influencing factors with the use of order data from a global semiconductor manufacturer. Customers want to receive their orders as expected since late and early deliveries will result in costs (Shen et al. 2023). In early deliveries, the semiconductors must be stored at the customer's location, leading to inventory costs. In case of late deliveries, missing semiconductors may disrupt the customer's manufacturing operations or, in the worst case, lead to a halt of production (Bushuev 2018). Hence, customers wish to receive an accurate prediction of when they can expect delivery. Communicating an accurate OLTc can help the semiconductor firm to maintain and improve customer satisfaction and retention (Knoblich et al. 2015). We aim to offer decision support for order management to communicate an accurate and data-informed OLTc within the supply chain of the semiconductor manufacturer and to its customers.

We compare three different linear regression models to understand which factors influence the OLTc that is determined during the semiconductor firm's order management operations. Our contribution is twofold. First, our results support an accurate prediction of OLTc and thus its reliable communication to customers. Second, we develop three specific managerial implications by analyzing influencing factors in supply chain planning and order fulfillment management.

Our findings indicate that the developed linear regression models are capable of accurately predicting lead time in general, in conventional business situations, and in particular settings where Standard Delivery Times (SDTs) are hard to determine. These settings are discussed in more detail in the following sections. Our results show that the Requested Order Lead Time (OLTr), the lead time of an order requested by a customer, is the most impactful influencing factor for analyzing OLTc. We demonstrate that splitting orders into Multiple Schedule Lines (MSL) leads to a rise in the OLTc and find that order price (*Price*) and ordered pieces (*Pieces*) have an opposite statement. Interestingly, *Price* can be used as a proxy when product-dependent lead time influencing factors are uncertain or difficult to obtain. Besides the general importance of our results to order and supply chain experts, we derive three specific implications on how to effectively manage OLT in the semiconductor supply chain based on the investigated influencing factors.

The remainder of the study is structured as follows: Section 2 considers previous related work. Section 3 delineates the research methodology, illustrating what lead time influencing factors have been considered and how linear regression is used to derive implications. Section 4 presents the results and discusses the implications for lead time management. Section 5 summarizes the main conclusions from the research and outlines potential areas for future research.

2 RELATED WORK

2.1 Background

Semiconductor manufacturing is characterized by multiple complex re-entrant process steps and capital-intensive production equipment, several sources of uncertainty, long cycle times, as well as long production and order lead times (Ehm and Ponsignon 2012; Mönch et al. 2011; Mönch et al. 2017). The semiconductor manufacturing process is divided by the die bank that serves as a buffer and decoupling point: While wafer fabrication in front-end is forecast-driven (make-to-plan), assembly and test operations in back-end follow make-to-order principles (Aelker et al. 2013; Herding and Mönch 2016; Lee et al. 1992; Mönch et al. 2011; Olhager 2010). Mönch et al. (2017) state that the time between the customer order decoupling point and order delivery should not be longer than the lead time that a customer expects for an order. Still, both the front-end and back-end are important to determine OLT, especially since chips spend more time in front-end than in back-end production.

Semiconductor manufacturers constantly need to balance the inventory of their highly customized products and the responsiveness (i.e., flexibility) expected by the customer to ensure delivery performance (Knoblich et al. 2015). Manufacturing operations are initialized based on an – ideally accurate – forecast of demand that can change over time. Such changes can provoke lead time changes (delivery delays, e.g.) that get amplified along the supply chain and can result in order cancellations, lost sales, and customer churn (Ehm and Ponsignon 2012; Jaenichen et al. 2021; Niemi et al. 2020). Determining (Mason-Jones and Towill 1999) and communicating (Lee et al. 1992; Li et al. 2015; Mönch et al. 2011) accurate lead time and lead time changes for orders can therefore help to manage customer expectations and satisfaction. Such reliable information exchange will more generally contribute to supply chain resilience, i.e., the capability of the focal firm to react effectively after disruptions (Chang and Lin 2019; Mahachi et al. 2022).

2.2 Related Research

Our study relates and contributes to the stream of research that predicts OLTs in semiconductor supply chain settings. We present relevant literature that covers different ways to approximate the prediction problem and provide a reasoning for our contribution to the field.

Studies in semiconductor supply chains with regard to lead times often focus on manufacturing settings or on manufacturing data. Schuh et al. (2019) present an order completion time prediction tool that can support manufacturing employees, with order completion time being defined as "the time from the release of an order to completion of the order" (p. 357). Mönch et al. (2011) investigate wafer fabrication to meet due dates communicated to customers and find that predictable cycle times support operations management. Li et al. (2015) use regression models to analyze manufacturing data to predict lead times. Burggräf et al. (2020) highlight the need for lead time prediction in complex manufacturing processes and use Machine Learning (ML) to predict manufacturing lead times based on material data in an engineer-to-order environment, emphasizing promising results of regression models. Lingitz et al. (2018) outline the need to extend manufacturing lead time prediction to other steps within the semiconductor supply chain and to analyze the semiconductor production in its entirety. They also find that linear regression can be used for lead time prediction and a detailed investigation of its influencing factors (Lingitz et al. 2018). As more data becomes available and computational efficiency improves (Easton and Moodie 1999), ML models can lead to promising results as well (Schuh et al. 2019). Shen et al. (2023) use real-world data sets to predict actual order lead times of semiconductors. To the best of our knowledge, Shen et al. (2023) are the first to incorporate data beyond the manufacturing context to predict order lead time, emphasizing the need for a quantitative analysis of a wider data range to determine influencing factors. Following the suggestions of Shen et al. (2023), this study extends the scope of analysis by investigating a wider range of order data and performing a systematic analysis of the parameters within the order data.

In summary, determining and communicating reliable lead time information is important to retain customers and increase supply chain resilience, especially in complex settings such as the semiconductor supply chain. Most recent research is concerned with predicting manufacturing lead time or using manufacturing data, thus concentrating on semiconductor fabrication in front-end. For accurately predicting the order lead time communicated to customers, we propose to include data that considers both the make-to-plan (front-end) as well as the make-to-order (back-end) portion of the semiconductor supply chain, as orders placed require both front-end and back-end processing. Against this background, we collect order data from the supply chain of the semiconductor firm and use linear regression models to understand the factors influencing OLTc. We extend the approach of Shen et al. (2023) and collect order data of a larger variety of products with additional variables over a longer time horizon (five years), and perform a systematic analysis of influencing factors within the examined regression models. The use of regression models allows a simple interpretation of the results and transparent decision support to supply chain experts (Hui et al. 2021; Lingitz et al. 2018; Rudin 2019). Therefore, the use of linear regression for this study can allow for a clear identification of OLTc and straightforward interpretation of influencing factors, thereby supporting an informed determination, effective management, and reliable communication of order lead times in the semiconductor supply chain.

3 METHOD

We collect order data from the semiconductor firm and predict OLTc using linear regression. The investigated data set contains customer- and product-specific information of orders. It contains the daily updated and latest available data for each order of the examined product range. In this section, we present our rationale for variable selection and the resulting data sets before we introduce the investigated regression models. For brevity, we introduce only those independent variables (influencing factors) with significant correlation (Pearson's Correlation Coefficient non zero at $p < 0.001$) to OLTc. All presented variables have pairwise Variance Inflation Factor (VIF) values below 2.5. Thus, we can rule out multicollinearity and include the variables in the regression models. (Harrell 2015; Olive 2017) Within the scope of this study, we did not consider detailed information on product family and packaging, or more detailed customer information due to data availability. As we argue later in this study, this information can be investigated in future research, potentially resulting in new findings.

3.1 Variables

If the delivery of certain items of an order has to be scheduled at different times, the order is divided into different schedule lines. Hence, we can observe multiple – requested and confirmed – lead times for a single order. Note that we use the Detailed Schedule Line Item (DSLI) as the unit of analysis in our study, as we can define a unique lead time on that level of detail.

Confirmed Lead Time. The dependent variable in our models is the confirmed order lead time, OLTc as defined in Equation (1). It is the time in days between the order entry, Purchase Order Date (POD), and the time at which the delivery of a DSLI is possible, Confirmed Delivery Date (CDD).

$$OLTc = CDD - POD \tag{1}$$

Customer Request. An important information to consider for predicting OLTc with data outside the manufacturing environment is the order lead time requested by the customer, OLTr, as defined in Equation (2). It describes the time in days between POD and the time at which the customer requests the order to be delivered, i.e., the Requested Delivery Date (RDD). The semiconductor manufacturer tries to meet the RDD as close as possible, which makes OLTr a useful predictor of OLTc.

$$OLTr = RDD - POD \tag{2}$$

The requested order volume also influences the lead time of an order (Cotteleer and Bendoly 2006; Shen et al. 2023). Therefore, we investigate the numerical variable *Pieces*, which indicates the number of ordered products per DSLI.

Order Fulfillment. OLTr and OLTc are determined when an order is placed, and are adapted according to dynamics in operations, such as changes in RDD or CDD during order fulfillment. The investigated order data includes the latest OLTr and OLTc based on RDD and CDD for each order. Consequently, we predict OLTc whenever a new promise is required to be issued. If a delivery cannot be guaranteed at RDD, the semiconductor firm proposes an OLTc to the customer that is longer than OLTr (Öner Közen and Ehm 2018). Yet, the order fulfillment operations at the semiconductor firm allow certain changes to the delivery dates after initial confirmation. When a customer requests an earlier RDD, CDD may be updated to an earlier point in time if the available supply allows earlier fulfillment of the order. If the ordered products will not be available at the previously determined CDD due to the circumstances at the semiconductor firm, the CDD can change to a later point in time, which better represents the supply situation. Due to those ongoing dynamics in manufacturing and order fulfillment operations, some delivery schedules may change (Aelker et al. 2013; Dörrsam et al. 2022). To capture the dynamics, the binary variable MSL tracks if an item of an order has at least two different delivery schedules, i.e., schedule lines. MSL is introduced as soon as an order is split, when certain parts of an order need to be delivered at different points in time: it is 1 if there are multiple schedule lines, and 0 otherwise.

Product Specifics. We find evidence in the literature that price correlates with order lead time (Cotteleer and Bendoly 2006; Shen et al. 2023). Therefore, we investigate the *Price* per DSLI as a variable within our model. As we observe the order data of a semiconductor firm with globally distributed sites, products are manufactured and stored at different geographic locations. Lead times can be region-specific (Cotteleer and Bendoly 2006) and we therefore investigate the categorical variable *Region*. It has four levels that indicate the location where products of a DSLI are manufactured or stored. Usually, each product has a specific standard lead time, SDT in weeks ($SDTnum < 90$), that is assigned at order entry and primarily depends on the product's manufacturing route. It can be an important source of information to determine OLTc and implicitly captures the duration of manufacturing operations. In some situations SDT is uncertain or cannot be obtained and therefore we introduce $SDTcat$ as categorical variable. It has three levels and indicates which situation causes the uncertainty about SDT: either (i) because a product is newly introduced to the market, (ii) it is at the end of life and will soon be discontinued, or (iii) the semiconductor firm faces a severe demand-supply mismatch for that product. The latter case can occur if supply is tight or demand surges.

3.2 Data

We collect order data from four selected product groups at the semiconductor firm over five years between 2018 and 2022 to ensure robustness against temporary influences on the semiconductor supply chain. Table 1 provides descriptive statistics of the selected variables after standardization.

Table 1: Descriptive statistics after standardization.

Variable	Count	μ	σ	Min.	Max.	Var.	VIF	ρ
OLTc	877,296	0.000	1.000	-2.356	1.383	1.000		
OLTr	877,296	0.000	1.000	-2.660	1.237	1.000	1.042	0.843
SDTnum	806,644	0.000	1.000	-1.705	1.522	1.000	1.055	0.246
Pieces	877,296	0.000	1.000	-1.687	2.130	1.000	2.205	0.126
Price	877,296	0.000	1.000	-1.603	2.006	1.000	2.202	0.151
MSL	877,296						1.004	0.179
...no	749,524							
...yes	127,772							

μ:Mean; σ:Standard Deviation; Min.:Minimum; Max.:Maximum; Var.:Variance; VIF:Variance Inflation Factor; ρ:Pearson correlation coefficient with OLTc.

After removing missing and invalid observations, the resulting data set $\mathscr{O}_{total}$ contains 877,296 entries, where each observation represents a DSLI. As the SDT contains both numerical and categorical variables, we investigate different data sets. First, we test all variables except SDT on $\mathscr{O}_{total}$. Second, we test *SDTnum* on the subset $\mathscr{O}_{SDTnum}$ ($n = 806,644$) where SDT is numerical. Third, we test *SDTcat* on the subset $\mathscr{O}_{SDTcat}$ ($n = 70,652$) where SDT is categorical. Note that $\mathscr{O}_{SDTnum}$ and $\mathscr{O}_{SDTcat}$ are mutually exclusive components of $\mathscr{O}_{total}$. Before applying the regression models, we standardize all three data sets. Winsorizing, logging, and scaling (Boudt et al. 2020; Cheng and Young 2023) reduce the impact of single features or outliers on the results. After standardization, $\mu = 0$ and $\sigma = 1$ for all numerical (dependent and independent) variables.

3.3 Models

The *OLTc* of a DSLI i is defined as the dependent variable $OLTc_i$, $OLTr_i$, $Pieces_i$, $Price_i$ (all numerical), MSL_i (binary), $Region_i$ (categorical), and SDT_i (categorical or numerical) of a DSLI i are defined as independent variables X_{ik}, where $k \in 1,...,7$ represents the individual independent variable. The resulting linear regression models are defined in Equation (3) for $i \in 1,...,n$, where n is the sample size, β_k are the fitted coefficients for independent variable X_{ik}, and e_i the individual error terms. We fit Model A on $\mathscr{O}_{total}$ and set $\beta_5 = \beta_7 = 0$, Model B on $\mathscr{O}_{SDTnum}$ with $\beta_7 = 0$, and Model C on $\mathscr{O}_{SDTcat}$ with $\beta_5 = 0$.

$$OLTc_i = \beta_1 OLTr_i + \beta_2 Pieces_i + \beta_3 Price_i + \beta_4 MSL_i + \beta_5 SDTnum_i + \beta_6 Region_i + \beta_7 SDTcat_i + e_i \qquad (3)$$

We assume that e_i are i.i.d. with expected value $E(e_i) = 0$ (Olive 2017). We validated that $E(e_i)$ are close to zero and that there is no strong evidence of significant autocorrelation in the residuals according to the Durbin-Watson statistic, supporting the assumption of independence. We test all models without intercept as it is unlikely that the *OLTc* results from the independent variables plus a fixed constant. If the independent variable increases by one standard deviation, with all other independent variables remaining constant, the dependent variable is expected to change by one standard deviation times the coefficient of the independent variable.

To build the prediction models, we perform hierarchical regression and add variables in the order of descending pairwise correlation coefficients with OLTc. In each step, we test whether the added independent variable significantly improves the model fit according to the Analysis of Variance (ANOVA) F statistic (Fein et al. 2022; Harrell 2015; Manderscheid 2017; Olive 2017). To make a robust statement whether the addition of a variable better approximates the prediction problem, we compare Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and R^2 (Fein et al. 2022; Kuha 2004; Manderscheid 2017; Olive 2017).

4 FINDINGS

The resulting Ordinary Least Squares (OLS) estimates of coefficients after step-wise determination of linear regression models Models A, B, and C are listed in Table 2. All listed variables show a significant improvement of model fit after their addition (ANOVA F statistic at $p < 0.001$, larger values for R^2, and smaller values for AIC and BIC).

Table 2: OLS results after step-wise determination of linear regression models. Note that only those additional variables are listed that significantly improve model fit according to ANOVA F statistic.

	Model A	Model B	Model C
$OLTr$	0.846***	0.840***	0.784***
	(0.001)	(0.001)	(0.002)
MSL	0.431***	0.360***	0.464***
	(0.002)	(0.002)	(0.005)
$Price$	0.062***	0.037***	0.128***
	(0.001)	(0.001)	(0.003)
$Pieces$	-0.063***	-0.036***	-0.111***
	(0.001)	(0.001)	(0.003)
$SDTnum$	not included	0.130***	not included
		(0.001)	
$Region$	included	included	included
$SDTcat$	not included	not included	included
n	877,296	806,644	70,652
R^2	0.741	0.765	0.655

Note. $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

4.1 Results and Discussion

Confirmed Lead Time. Model A, developed on $\mathscr{O}_{total}$, demonstrates that 74.1% of the variability in OLTc can be explained by the variables included in the model, independent of product life cycle and business situation ($R^2 = 0.741$). To predict OLTc in regular situations (standard delivery time < 90 weeks), Model B is developed on $\mathscr{O}_{SDTnum}$. Model B can be used to explain 76.5% of the variability in OLTc ($R^2 = 0.765$). This is an improvement compared to Model A. For situations when products reach end of life, are newly introduced or standard delivery times are unreliable due to demand-supply mismatches, we develop Model C on $\mathscr{O}_{SDTcat}$. Although these situations are characterized by substantial uncertainty, Model C can still predict OLTc relatively well ($R^2 = 0.655$). The large R^2 values for models A, B, and C indicate that it is possible to explain a reasonable degree of variance in OLTc with linear regression. Such models can be useful in practice as they offer a more nuanced and data-informed understanding of OLTc, which is not mainly reliant on tacit knowledge. Note that, across models, the coefficients of independent variables point into similar directions and exhibit similar magnitudes, which further indicates robustness and explanatory power of those selected variables.

Customer Request. The coefficients of the independent variables indicate that $OLTr$ has the strongest influence on $OLTc$ in each model. While the $OLTc$ is always larger than the $OLTr$, the high coefficients of the *OLTr* show that the semiconductor firm aims to offer its customers an *OLTc* close to the *OLTr*. Plausibly, the requested delivery date has a larger influence in conventional situations (Model B) than in particular situations (Model C), where confirmed and requested lead time may deviate more. *Pieces* is negatively correlated with *OLTc* in each model, demonstrating that if the number of products in an order increases, the *OLTc* decreases. Dividing production lots into smaller units to fulfill individual orders is time-intensive for the semiconductor firm. High order volumes are therefore more attractive and the corresponding customers of higher importance. Those customers usually receive shorter lead time confirmations than customers with a lower order volume. The effect of *Pieces* on *OLTc* is most pronounced in particular situations (Model C), as prioritization of customers (by order volume, e.g.) may play a more important role for the semiconductor firm when order fulfillment situations are more uncertain. Yet, as the coefficient of *Pieces* is relatively small, the size of an order does not strongly increase its *OLTc* compared to the other independent variables included in the models. Consequently, overall the delivery date requested by customers is more important to determine *OLTc* than the requested order volume.

Order Fulfillment. The medium coefficient of *MSL* across models indicates that splitting the order into multiple deliveries results in an increased *OLTc* for those split orders. This finding is plausible as the reasons for multiple delivery schedules per order are usually rooted in operational dynamics that interfere with initial delivery plans and may prolong lead times. In particular, MSL can indicate that (i) the requested volume of products is not available at the RDD and some items of the order may be delivered later (i.e., with longer *OLTc*); (ii) as shipping costs for split delivery plans increase, choosing a more cost-effective shipping mode may lead to longer shipping times (i.e., with longer *OLTc*); or (iii) updating delivery plans and thus additional coordination in order fulfillment management increases the time until products get manufactured or dispatched (i.e., with longer *OLTc*). The smaller coefficient of MSL in conventional situations (Model B) demonstrates that splitting orders into multiple deliveries is a common practice at the semiconductor firm that does shorten lead times less than in situations that require particular attention (Model C) and thus more time-consuming order fulfillment operations.

Product Specifics. The *Price* of an order is positively correlated with *OLTc*. This effect is mainly rooted in semiconductor manufacturing particularities that are product-dependent. Complex products, which are usually offered at higher prices, require longer production times compared to simpler products and thus result in longer *OLTc*. In regular situations (Model B), *SDT* has a larger influence on *OLTc* than *Price* and captures the product-dependent lead time better. Still, the effect of *SDT* on *OLTc* is smaller than the effect of *OLTr*. We also find that the variation of *SDT* for different products is rather small, especially for similar types. This finding is important as it demonstrates that the product-dependent manufacturing specifics may only account for a fraction of the variation in *OLTc*, while the delivery date requested by customers and order fulfillment details are more important to determine *OLTc*. Interestingly, in particular situations where SDT cannot be determined (Model C), the *Price* of an order has a larger effect on *OLTc* than in Model B. *Price* can therefore serve as a proxy variable when product-dependent lead time influencing factors are uncertain or difficult to obtain.

4.2 Managerial Implications

In general, we offer support to practitioners who are interested in accurately determining lead time and its influencing factors in the semiconductor supply chain. Our results demonstrate that only product- and production-specific information does not explain the OLTc sufficiently and that customer requests and order fulfillment practices have to receive increased attention to determine a reliable OLTc. In addition, a more accurate determination of OLTc can help supply chain planners or order managers to detect any deviations between a customer's wish and the confirmed delivery, which can support their decision making. Besides this general guidance, we can derive three specific implications for managing lead times effectively in the semiconductor supply chain.

First, the strong influence of OLTr on OLTc indicates that suppliers of semiconductors have an inherent interest in fulfilling the wishes of customers, and that the make-to-order section of the internal supply chain plays an important role in determining the OLTc. All the more important are reliable and accurate demand signals from customers to inform the manufacturing planning decisions of the focal firm, as it will strongly influence the OLTc. Nudging customers to provide more accurate requests of delivery dates (and quantities) builds upon communication and trust. Since small changes in OLT can be amplified throughout the semiconductor supply chain, communication between the different parties can increase supply chain resilience and combat the influence of disruptions (Agrawal et al. 2009; Jaenichen et al. 2021; Lee et al. 1997). Consequently, collaboration and information transparency in supply chain management can lead to increased coordination between companies, reduced demand variation, and improved order management practices that support supply chain resilience (Agrawal et al. 2009; de Almeida et al. 2015; Dörrsam et al. 2022; Pettit et al. 2010). We argue that a more accurate lead time communication to customers increases trust into the intentions of the semiconductor firm and thus collaborative behavior of customers (with more reliable demand signals) will become more likely.

Second, supply chain planners and order fulfillment managers should pay close attention whenever multiple delivery schedules of an order are initiated. To manage lead times effectively, it is necessary to monitor and track individual delivery schedules of orders and communicate changes in delivery plans to customers. Moreover, order fulfillment managers could communicate a general possibility for increased OLTc to customers after MSL are introduced for an order. Although introducing MSL may be necessary under certain circumstances, avoiding this practice can substantially shorten OLTc. We propose a careful consideration and readjustment of conditions that lead to MSL. Nevertheless, such consideration is a double-edged sword. The partial fulfillment of an order at an earlier (i.e., requested) point in time can also increase customer satisfaction and lead to a longer lead time for only some items of that order. It will be important to capture customer-specific reactions to partial deliveries and their different OLTc, for instance by investigating behavioral patterns of customers as in Ratusny et al. (2022).

Third, particular situations need particular considerations to determine OLTc, as shown in Model C. As products are newly introduced, arrive at their end of life, or tense market situations do not allow a reliable SDT estimate, other lead time management and determination strategies are required. While such guidance may sound obvious at first sight, we find it important to emphasize that in those particular situations not only customer requests cannot be fulfilled as usual but the practice of introducing multiple schedule lines has a larger effect on OLTc (in Model C) than in Models A or B. Consequently, a careful consideration of conditions that lead to the introduction of MSL is vital in such uncertain situations. We propose to capture the small fraction of product-dependent specifics that determine OLTc by introducing *Price* as a dummy variable when SDT cannot be obtained reliably. Additionally, consulting order fulfillment managers and supply chain planners can support an accurate estimate of OLTc, which is feasible for the relatively small amount (<10%) of orders in those situations.

5 CONCLUSION

OLTc is initially determined at order entry and is also dynamically adapted after an order has been placed. As changes in order data can result in changes in the actual order lead time that get amplified along the supply chain, determining a new and accurate OLTc is very important. Our model can help to determine a data-informed estimate of OLTc based on the changes in order data during order fulfillment. This decision support can be especially valuable in times of allocation due to tight supply. Communicating this predicted OLTc within the supply chain can increase supply chain resilience, and communicating the new OLTc to customers can help to manage customer expectations and satisfaction. To overcome shortcomings of recent research on OLT and its influencing factors, we collect data of more than 800,000 orders from a global semiconductor manufacturer that captures both make-to-plan and make-to-order information within the internal supply chain. Our contribution is twofold.

First, our results support an accurate prediction of OLTc. We develop three linear regression models: one general, one conventional, and one model for particular situations where SDTs are hard to determine. Consequently, we ensure reliable communication of OLTc in the semiconductor supply chain by considering a data set containing information throughout the front-end and back-end. All three models can predict OLTc relatively well (R^2 values between 0.655 and 0.765). Using linear regression as a white box ML approach enables a straightforward determination and interpretation of the influencing factors of OLTc, a shortcoming identified in previous research (Shen et al. 2023). We find that the semiconductor firm aims to offer its customers an OLTc close to the OLTr, demonstrate that splitting orders into MSL leads to a rise in OLTc, and show that product-specific information has rather low effects on OLTc.

Second, we derive three specific implications for how supply chain planners and order fulfillment managers can effectively manage lead time in the semiconductor supply chain. They are based on an in-depth analysis of the identified influencing factors that significantly correlate with OLTc: OLTr and order volume as requested by the customer; individual scheduling decisions during order fulfillment captured by MSL; and product specific SDT, order price, and manufacturing region. We confirm that the semiconductor firm tries to adhere to requested or contractual lead times, see also Knoblich et al. (2015), conclude that accurate demand signals to inform the manufacturing planning decisions of the focal firm are all the more important, and give some ideas for nudging customers to provide such reliable demand signals. Further, supply chain planners and order fulfillment managers should pay close attention whenever multiple delivery schedules of an order are initiated, communicate such situations to customers to raise awareness of potentially deviating OLTc, and carefully readjust conditions that lead to an introduction of MSL. Additionally, we emphasize that in particularly uncertain situations (in Model C) not only customer requests cannot be fulfilled as usual, but the practice of introducing multiple schedule lines has a larger effect on OLTc. Interestingly, *Price* can be a proxy when product-dependent lead time influencing factors are uncertain or difficult to obtain.

While our analysis includes a larger time horizon, a more diversified selection of products and additional variables compared to Shen et al. (2023), we propose to test the robustness of our results across an even larger selection of products. In the same vein, it will be interesting to investigate market-specific OLT prediction models that can be tailored to specific product families. The developed linear regression models can already provide a good predictive performance, yet future research should apply more advanced models to the data if prediction performance is particularly important and to understand whether nonlinear relationships exist within the data.

The proposed models do not explain all the variance in OLTc. The consideration of additional data and its integration in the model can be a meaningful extension of the study. To further increase predictive performance, we propose to include exogenous variables to the models that capture relevant aspects such as seasonality or market dynamics.

Palaka et al. (1998) investigate quoted lead-time, capacity utilization, and price in a model of a firm's operation for lead time sensitive customers. While we already consider price in relation to OLTc as a factor indicating product complexity and production process steps, in future research capacity utilization and job priority could be investigated. The influence of price on OLTc can be further investigated by including information on the packaging of the ordered semiconductor, such as the orientation of the chip or the number of pins connecting the semiconductor surface to the circuitry of a device. For instance, packaging information could be used to receive an understanding of how the specific manufacturing of the semiconductor influences the OLTc of a semiconductor order. Moses et al. (2004) suggest the consideration of order priority in order promising. Investigating the influence of customer order priority (customer class or the position of the customers in the value chain) is a promising direction for future research. Furthermore, such augmentations of the prediction model can particularly support the prediction for Model C, where the semiconductor firm faces increased uncertainty in order fulfillment operations. We want to emphasize that understanding customer behavior can inform the selection of lead time management strategies. It will be interesting to understand how customers actually react if they are confronted with OLTc that is (much) longer than their initial request. Such deviations may even be used as indicator for customer satisfaction as some of the customers might accept the deviations, while others might complain if such deviations severely affect their own operations. In future research, it could also be investigated whether extending the model with additional independent variables outside the focal firm is feasible, such as with supply-side data, as considered by Seitz and Grunow (2017) for order promising. In order to generalize our findings, it will be interesting to test the presented prediction models with data from other companies or in other industries, where similar characteristics as in the semiconductor supply chain are present.

The results of this study have implications for managing lead time influencing factors, lead time communication and supply chain resilience. The identified and measured factors can assist with decisions in the semiconductor supply chain, especially for lead time and order fulfillment management, and supply chain planning. An increased understanding of order lead time and its influencing factors can sustainably contribute to more stable and resilient supply chain operations. While customers benefit by reliable communication of lead time for their supply chain planning, the semiconductor firm can use our results to effectively manage lead time and maintain customer satisfaction and retention.

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