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An Empirical Analysis of Forecast Sharing in the Semiconductor Equipment Supply Chain

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1. Introduction

Sharing demand forecast information has been recognized as a key element in supply-chain coordination (Cachon and Lariviere 2001). Over the last decade, companies have engaged in various forecast-sharing practices, including the Collaborative Planning, Forecasting, and Replenishment (CPFR) initiative, which was launched to "create collaborative relationships between buyers and sellers through comanaged processes and shared information."[1] Retailers such as Wal-mart and Best Buy, along with suppliers such as Procter & Gamble and Kimberly-Clark, have all reported positive benefits from CPFR projects. For example, GlobalNetXchange, a consortium consisting of over 30 trade partners, including Sears, Kroger, Unilever, Procter& Gamble, and Kimberly-Clark, have reported achieving a 5–20% reduction in inventory costs, while improving off-the-shelf availability by 2–12% after successfully launching their CPFR programs (VICS CPFR Committee 2002).

Despite these success stories, forecast sharing still suffers from several problems in practice. While, *ceteris paribus*, it is always desirable to have more information, the sharing of forecast information lends itself to two types of problems. First, forecasts change and are continually updated as the buyer receives new information. This leads to the question of determining the point where the provided information is sufficiently accurate to justify acting on it. A supplier who will act immediately on a given forecast will likely face future adjustment and rework costs.

Second, forecasts provide information about what the buyer intends to do in a given future state of the world. These intentions, however, are not verifiable and cannot be enforced. This is a setting of asymmetric information, and it makes contracting based on forecasts difficult. Specifically, previous analytical research has suggested that the buyer has an incentive to inflate forecasts to assure sufficient supply (Cachon and Lariviere 2001).

The extent by which forecast inflation is optimal for the buyer depends on the relevant planning horizon. Recent analytical research on supply-chain contracting has focused on one-shot games. As we will observe, playing a one-shot game repeatedly can lead to different equilibria.

[1] Website: ⟨www.cpfr.org⟩.

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In the capital-equipment context studied here, the single-period game requires the buyer to place a forecast order. The supplier is then required to allocate a certain amount of production capacity and to commit to the purchase of long leadtime-input components, possibly prior to receiving a firm order (purchase order). As we demonstrated in an earlier paper (Cohen et al. 2002), the single-period game induces the buyer to over-forecast and the supplier to under-deliver by delaying the initiation of a production order.

In this paper we consider a multiple-period perspective to further explain this undesirable outcome. We demonstrate, in particular, that in choosing capacity allocation, the supplier not only considers the current forecasts placed by the buyer, but also considers to what degree the buyer has a history of being reliable (i.e., makes few forecast changes) and trustworthy (i.e., does not inflate the forecast quantity). Specifically, our work is the first to show empirically that:

- A supplier who has experienced forecast due-date changes from a buyer in the past will be less willing to allocate capacity to meet that buyer's orders based on a preliminary forecast.
- A supplier who has experienced a greater amount of order cancellation (i.e., over-forecasting) will also be less willing to allocate capacity to that buyer's orders based on a preliminary forecast.

Our empirical findings complement the rapidly growing literature of analytical models of procurement and contracting. Although several articles have pointed to the problem of inflated forecasts, the proprietary nature of order-fulfillment data makes it difficult to demonstrate such effects empirically. Moreover, given the dynamic nature of the fulfillment process, it is necessary to look at a sequence of forecasts and deliveries. The paper is the first to analyze data linking the history of shared forecasts provided by the buyer with the delivery performance provided by the supplier.

These research findings have important implications for forecast-information sharing in general. While from the static perspective, inflating forecasts is in the interest of the buyer, our results demonstrate that this short-term advantage comes at the price of receiving a lower level of service. Indeed, future supplier performance is affected by the "reputation" of the buyer.

Our study is grounded in detailed data on forecast sharing and order fulfillment that was collected in the semiconductor equipment supply chain. Given the long manufacturing leadtimes of such equipment, as well as the highly customized nature of the technology, buyers and suppliers routinely share forecasts about future needs for equipment acquisition. Intense coordination between buyer and supplier is especially important in the semiconductor equipment supply chain, due to the large amount of uncertainty in the volatile market for microprocessors as well as the complex, rapidly evolving technology of wafer processing.

2. Research Objectives and Key Hypotheses

Our objective is to identify the conditions under which the practice of forecast sharing leads to on-time tool deliveries, despite the fact that production leadtimes exceed the requested leadtimes specified in the final purchase order. For that purpose, we form the following series of hypotheses.

Hypothesis 1. *Deviation from supplier's preferred order leadtime will result in delay in actual leadtime.*

The above hypothesis can be stated with the aid of the Figure 1(a). In the graph, t^* is the supplier-preferred leadtime, i.e., the point where suppliers can match requested delivery time. A longer requested LT ($t^* + \Delta$) would result in a even longer supplier leadtime ($t^* + \Delta' > t^* + \Delta$), while a shorter requested leadtime ($t^* - \Delta$) would yield delay as well, i.e., $t^* - \Delta'' > t^* - \Delta$.

When the supplier decides to what extent she is willing to commit resources early, based on a soft order she has received, she is likely to consider two properties of the forecast history she has seen to that point. One is frequent due-date changes:

Hypothesis 2a. (Effect of Due-Date Changes). *The more the customer changes the RDD (requested due-date) of a particular soft order, the more likely it is for* that *order to be delayed.*

A graphical presentation of this effect is depicted in Figure 1(b). Consider two orders: Order A and

Figure 1(a)

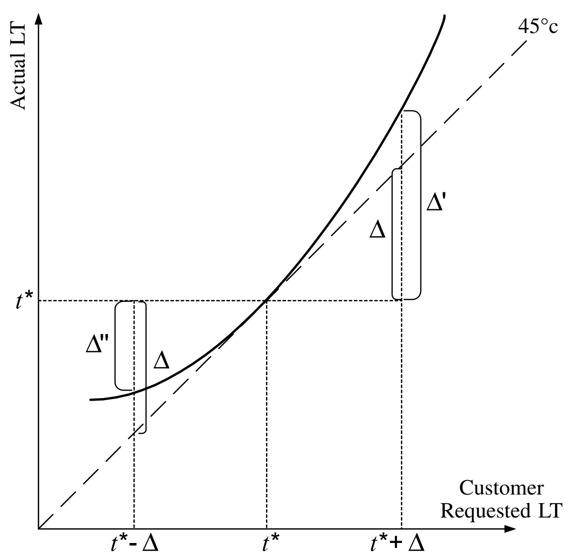
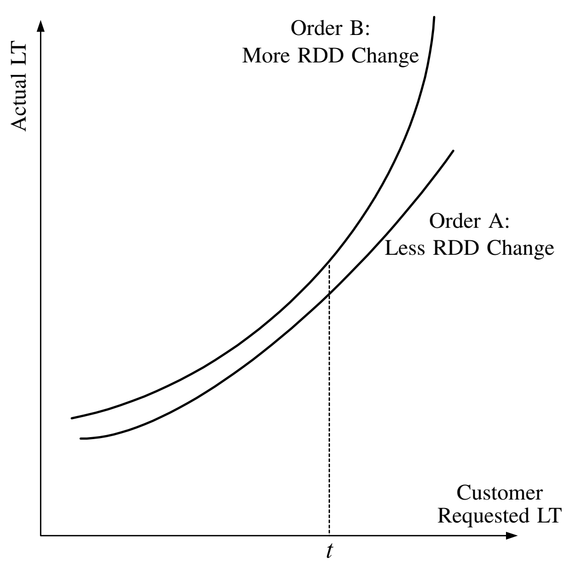


Figure 1(b)



Order B. Suppose they are for two identical tools, made by the same supplier, and they both request the same order leadtime t from the same supplier. The only difference between the two is that Order A has less RDD changes (push-out or pull-in) before its PO is placed, while Order B has gone through more changes. We conjecture that Order A would be delivered earlier than Order B.

Moreover, we distinguish between long-term and short-term effects of RDD changes. By a short-term effect we mean RDD changes of one particular order will affect the leadtime of that specific order. A long-term effect on the other hand means that RDD changes of previous orders can affect the leadtime of the current order. This long-term effect is attributed to the supplier's learning about the buyer's reputation. Hence we posit the following:

Hypothesis 2b. *The more the customer has changed RDDs for his soft orders in the past, the more likely it is for his* current *order to be delayed. That is, suppliers learn from the past behavior of the customer regarding changes, and react to such past change by delaying current orders.*

A second reason why a supplier might not be willing to initiate work for a soft order relates to the perceived probability of order cancellation. We therefore posit our next hypothesis on the effect of order cancellations:

Hypothesis 3a. (Effect of Order Cancellations). *Past soft-order cancellations, i.e., order-forecast deletions, prolong current order leadtime. That is, the more frequently the customer has cancelled soft orders in the past, the more likely it is for the supplier to delay production leading to a longer order leadtime.*

Similarly if two soft orders are identical in every respect except that one is forecasted during economic downturn and the other is forecasted during economic upturn, then we would expect the latter would experience more delay. Hence:

Hypothesis 3b. *The delay from order cancellation is more severe during an economic upturn when capacity is constrained.*

3. Methodology

Each order goes through the sequential process of: (1) being forecasted ("soft orders"); (2) being purchase-ordered (POed, or "hard-ordered"); and (3) being completed, either being delivered or cancelled. Our model is thus formulated in two stages. The first stage concerns "order evolution," i.e., the evolution of a forecast into an actual purchase order (PO). Then, conditional upon that event, the second stage models the duration between PO placement and completion.

The first stage is a multinomial logit model, whose discrete outcome for a forecast is either converting to PO, deletion, or remaining as a forecast. Once an order is placed, the variable of interest is how long the customer has to wait before receiving a delivery. Here we model durations using a hazard model. Moreover, in modeling we address the following issues:

- Data are right-censored, i.e., observations on duration are truncated at a fixed point in time;
- An order could be cancelled during its production stage after a PO has already been issued. Thus, an order can be finished either due to delivery or cancellation. In other words, its duration can have multiple outcomes;
- In a manufacturing environment, the manufacturing leadtime of one order could well be dependent upon the leadtime of those orders queued in front of it in the manufacturing pipeline.

To address those issues, we extended the hazard model to the situation where observations are non-independent, and built a structural, logit-embedded proportional hazard model that takes into account correlation among orders as well as competing risks of order cancellation and delivery.

4. Results

We found that indeed the supplier has a preferred order leadtime at around six to seven months. Therefore Hypothesis 1 is accepted. We also found that when the customer shares inflated order forecasts ("soft orders") that are subject to frequent cancellation and due-date changes, the suppliers prolong their delivery leadtime. Thus, Hypothesis 2 and 3(a) are accepted. So is Hypothesis 3(b). For example, for a tool with six-month requested leadtime, a 1% increase in cancellation probability would on the average induce 1.2 days of additional delay during an economic downturn and 3.9 days of delay during an economic upturn. Moreover, each additional day of due-date change made by the supplier to past orders would lead to 0.3 days of additional delay in the current order.

In this study, we find that both over-forecasting and introduction of forecast changes have a negative impact on the order leadtime. Over-forecasting and forecast changes make suppliers trust customer's forecasts less. Forecast changes, moreover, can disturb a supplier's production schedule leading to increased costs. Therefore, suppliers prefer to delay order fulfillment, resulting in longer order leadtimes when responding to customers whose forecast information is considered less reliable. Our finding is counter to the common perception that forecast sharing always benefits the supply chain. Our analysis indicates that the sharing of inflated, risky, and/or volatile forecasts can lead to degraded performance from the perspective of both the buyer and supplier.

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