Managing Short Life-Cycle Technology Products for Agere Systems

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Over the past decade, the high-tech industry has been rapidly innovating technology and introducing new products. Firms have moved from vertically integrated operations to horizontally integrated operations that include contract manufacturers. In September 2002, Agere Systems recognized that it needed new tools for managing the capacity in its increasingly complex, global supply chain. Agere and the Center for Value Chain Research at Lehigh University formed a team to develop new methods for characterizing the demands for short life-cycle technology products. The team developed a leading-indicator engine that identifies products that provide advanced warning of demand changes for a group of products. For a data set including 3,500 semiconductor products, the analysis identified leading indicators that predicted the demand pattern of the product group one to seven months ahead of time with correlation values ranging from 0.51 to 0.95. The leading-indicator concept provides a new perspective on demand forecasting and can be extended to other corporate planning functions, such as financial forecasting and inventory forecasting.

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In the mid to late 1990s, high-tech industries, such as consumer electronics, telecommunications equipment, and semiconductors, grew rapidly. Many firms developed and deployed supply-chain-management systems to integrate and optimize their operations. To reduce costs and cycle times, they focused on internal integration but continued to rely on traditional demand planning in which their marketing departments adjusted the projections of customers to forecast the number of units operations should produce. While the dot-com boom fueled demand growth, using customer-driven marketing forecasts for planning was adequate, because companies were more concerned with meeting demand and ensuring that products were available than with the accuracy of the data that customers provided. However, because of this approach to planning, many companies did not react quickly to the industry decline in 2001. With the decline initially predicted to be short lived, many customers were reluctant or slow to revise their forecasts. Many suppliers were reluctant or unable to penalize their customers for canceling orders and had to reconcile optimistic forecasts with increasingly negative economic indicators. By the time the industry acknowledged the depth and potential duration of the decline, many companies had to assume financial responsibility for large buffers of inventory and underutilized capital equipment, further depleting their cash reserves.

Demand for high-tech products is always volatile and challenging to manage; rapid innovation causes short product life cycles, and long production lead times hamper firms’ ability to respond. When demand grows steadily, supply chain partners might build inventory or hold excess capacity to buffer against demand variability, but many will not assume this financial risk in a slowing market. Firms recognize, however, that they must provide innovative products and exceptional service to retain customers and to gain new revenue opportunities. They must structure their supply chains to respond to upside demand and to absorb downside risks without...
creating excessive inventory or capacity. For this reason, the high-tech industry has transformed itself during the past decade, expanding in the mid-1990s and contracting in the early 2000s.

Major corporations now focus on those parts of the product-realization process in which they hold the strongest value proposition instead of owning and operating the entire process. Many are moving from vertically integrated operations to horizontally integrated operations that include contract manufacturers. In such a restructured supply chain, a customer (for example, Cisco Systems) may subcontract its manufacturing to multiple contract manufacturers, with each subcontractor placing orders with the component suppliers (for example, Agere). By consolidating many customers’ demands and by developing and investing in flexible processes, contract manufacturers can achieve high utilization on their equipment, thereby reducing unit costs. Also, by consolidating the procurement of components for multiple customers, contract manufacturers obtain economies of scale from their suppliers. Thus, contract manufacturers can offer their customers a greater variety of products at lower costs. The share of manufacturing done on a contract basis is expected to grow as more firms outsource a larger share of their manufacturing. In the semiconductor industry, contract manufacturing is expanding beyond companies without wafer fabrication facilities as even fully integrated component suppliers are beginning to contract their front-end (wafer fabrication) operations to assembly and test facilities or contract their back-end (packaging) operations to assembly and test facilities or contract their front-end (wafer fabrication) operations through partnerships with major foundries. The value of the electronics manufacturing services market is expected to increase from $138 billion in 2003 to $294 billion in 2008 (Carbone 2005), and double digit growth rates are predicted through 2010 (Jorgensen 2005).

The shortening product life cycle and the emergence of contract manufacturing reflect broad trends in the global economy toward rapid product innovation cycles and increasingly complex manufacturing and supply chain partnerships. High-tech contract manufacturers are concentrated in the Asia-Pacific region and are economic drivers for China, Taiwan, Korea, and Malaysia. The major ports of Hong Kong and Singapore have become logistics consolidation points for many of these operations.

In September 2002, Agere Systems recognized that it needed new tools for managing the capacity in its increasingly complex supply chain. Agere and the Center for Value Chain Research at Lehigh University formed a team to study the issue. Agere sought recommendations for new methods for characterizing the demand of short life-cycle technology products and for decision-support tools for capacity planning and negotiation with their global supply partners.

### Agere’s Products and Business Environment

Originally the microelectronics division of Lucent Technologies, Agere Systems was spun off from Lucent in March 2001. Agere specializes in providing semiconductor products for wireless data, high-density storage, and multiservice networking markets. Its wireless data products include general packet radio service (GPRS) chips that provide Internet connectivity for cellular phones and wireless voice over Internet Protocol (IP). In the high-density disk-drive market, the company is the leading provider of chips for hard-drive drives, including read channel, preamplifiers, and systems-on-a-chip that integrate several functions into a single device. In the telecommunications infrastructure market, the company provides custom and standard integrated circuits (ICs) for multiservice networking equipment that moves information across wired, wireless, and enterprise networks.

Agere’s business is organized by product lines into four business units: Enterprise and Networking, Mobility, Storage, and Telecommunications. Each business unit is subdivided into business entities based on product technologies. Each business entity serves a particular technology market, and each market tends to follow a particular pattern and rate of technological evolution. For instance, the technology life cycle for custom ICs on cellular phones is quite different from that for the motor controller ICs for hard drives. New technologies are accepted more readily in the cell-phone market and replaced more frequently, creating shorter product life cycles.

As is typical in semiconductor manufacturing, Agere’s operations consist of two main stages. In the front-end operation, silicon wafers are fabricated in clean-room facilities (fabs), and in the back-end operation, wafers are cut, packaged into IC chips, and
tested. The front-end operation has a manufacturing lead time of six to 12 weeks and typically is the bottleneck, while the back-end operation requires two to four days. Many semiconductor manufacturers outsource the front-end operation and become fabless because the wafer fabs are capital intensive and take a long time to build. A typical fab costs $1 to $4 billion and takes 12 to 18 months to build. Although Agere retains some fab capabilities in-house, foundry partners, such as Chartered Semiconductor and Taiwan Semiconductor Manufacturing Company (TSMC), handle most of the front-end operation. Agere’s facilities in Asia typically perform the back-end operations.

Manufacturers like Agere, whose capacity is largely owned by outside foundries, must predict market conditions accurately to ensure that capacity will be available when they need it. Characterizing product demands, however, is difficult for companies like Agere that are part of a complex global high-tech supply chain. Agere’s customers include personal computer (PC) manufacturers (for example, Apple Computer), wireless handset providers (for example, Samsung Electronics), network equipment suppliers (for example, Lucent and Cisco Systems), and manufacturers of high-density storage devices (for example, Maxtor). Many of these firms now rely on contract manufacturers. Instead of receiving a single data feed from each customer, Agere now receives a data feed from each of the customer’s manufacturing facilities and contract manufacturers. The multiple data feeds arise because each customer splits demand across multiple subcontractors, who in turn individually request components from suppliers (Armbruster 2002). For Agere, the multiple sources of demand data create complex demand characteristics and require multiple inventory buffer locations. Clearly, this structure affects planning, and Agere needs new methods for characterizing demands. In a separate research project in collaboration with an Agere customer, we studied the inventory strategies for consolidating multiple demand feeds, increasing inventory turns, and increasing transparency.

One operations manager summarizes his perspectives on Agere’s situation as follows:

The planning and coordination environment for our industry is extremely complex and difficult to manage due to the exceptionally volatile nature of product demands and the complex manufacturing processes. In addition, the semiconductor supply chain has to constantly battle with short product life cycles and capital intensive capacity that requires a long lead time for expansion. … Our objective is to more accurately anticipate our market conditions, better estimate production capacity needs in order to procure the appropriate manufacturing capability and make optimum use of our capital assets. Improving how we plan and make decisions in this industry will also contribute to the success of our customers. For example, achieving early production ramp for custom logic IC for our customers in the multimedia computing or communications equipment markets will help them to strengthen their competitive advantage.

Exploring the Research Questions

High-tech manufacturing is driven primarily by time-based competition. A manufacturer’s ability to supply customers responsively and flexibly defines its competitive advantage. In our project, we focused on demand-characterization tools that will allow Agere to handle demand signals proactively so that it can obtain the right level of capacity for the right time, known as supply-demand planning. We addressed the following questions.

(1) Can we identify patterns from historical or current demand data that enhance our understanding of high-tech demands? Can we identify leading indicators that provide advanced warning of demand changes? Can we find ways to identify and monitor these leading indicators?

(2) Can the leading indicators (if they exist) produce reliable demand forecasts? Can we develop general-purpose analysis tools based on the concept of leading indicators? Can we determine whether a particular group of products is a strong leading indicator for a set of products?

Understanding the Volatility of High-Tech Demand

Agere and other high-tech manufacturing firms know that the compressed technology life cycle and the complex supply structure have overwhelmed their supply-demand planning systems. We began our study by examining the demand information stored in Agere’s order-management system. For each product, the system tracks a customer’s orders for a
shipment in an upcoming week; these orders are referred to as the backlog or the order board. Because customers can change order quantities until the order is shipped, the snapshot as of February 28 of the order board for shipments for the week of March 14 to 18 may differ from the snapshot as of March 7. To understand the volatility of the demand, we reconstructed from historical data the weekly views of the order board over a 14-month period in 2001 and 2002 for a representative sample of Agere’s products in telecommunications, personal computing, and storage.

For each shipment of each product, we reconstructed the sequence of weekly views of the order quantities and computed their mean values. Then, we compared the mean values to the quantities shipped and computed the percentage deviation (the difference between the mean value and the actual quantity divided by the actual quantity) (Figure 1). Both the percentage of deviation and the number of occurrences are alarmingly high, indicating a volatile market for which order-board data is a poor predictor of shipments. The order-management system also stores the demand forecast, which the marketing department produces and updates monthly. If we reconstruct the sequence of monthly views of the forecasted order quantities and compare the mean forecasted value to the quantity shipped, the deviation is significantly greater than that of the order-board data.

Many operations managers are resigned to the fact that demand is too volatile to forecast. A common belief is that timely information updates, reduced lead times, and well-controlled operations enable orders from the order board to drive production. However, the order-board data may be unreliable. For long-term planning, Agere needs a comprehensive characterization of demand, despite the difficulty in constructing one. For specialized semiconductors, technological barriers limit the reduction of production lead times, and firms have no way to build finished-goods inventory, because most IC chips are customized for special functionality. Planning is crucial to combating demand uncertainty both for expanding in-house capacity and for negotiating and reserving outsourced capacity.

Traditional time-series forecasting methods work best when demand trend is stable. Demand for high-tech products can vary tremendously during the

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**Figure 1:** For 560 products shipped during a 14-month period, we computed the percentage deviation between the mean order quantity and the shipment quantity. We grouped the products according to their percentage deviation. For each percentage range, the bars show the number of products. The line plots the cumulative percentage of products whose percentage deviation falls below a particular value. The left half of the histogram represents the case of a negative deviation where the actual shipment is lower than the mean order quantity. The right half represents positive deviation where the actual shipment is higher than the mean order quantity.
different stages of their life cycles. Therefore, time-series forecasting methods based on historical demands do not yield satisfactory results for high-tech products (Skiadas 1986, Mahajan et al. 1990, Sharma et al. 1993, Islam and Meade 1997). Operations researchers have recognized the needs for special methods to deal with short life-cycle products (Fisher and Raman 1996, Kurawarwala and Hirofumi 1996). After analyzing Agere’s shipment data using nine time-series forecasting methods (Wu et al. 2003), we confirmed the need for special methods.

The Leading-Indicator Analysis

We tried to discern patterns in historical or current demand data to enhance our understanding of Agere’s demand. Specifically, we looked for leading indicators that would predict major changes in demand. From 1997 to 1999, we analyzed the demand data of Lucent Technologies’ microelectronics division (now Agere) for some 3,500 products (Meixell and Wu 2001). We found that the 3,500 products analyzed followed six life-cycle patterns, and we grouped the products according to the patterns using statistical cluster analysis. After performing correlation analysis on historical shipment data, we found in each cluster a subset of leading indicator products that predicted changes in demand for the cluster. The demand pattern of a leading indicator is correlated with that of the group, but the group’s demand pattern lags behind that of the leading indicator (Figure 2).

Technology life cycles for high-tech products start with an initial growth (ramp up) followed by a period of stability and then a decline in sales when a new generation of products is introduced. A product’s life cycle is driven by technological innovation and market competition. The traditional time-series forecasting approach is ineffective for high-tech products because their life cycles are so short that the demand trend in historical data cannot be expected to continue. The leading indicator analysis provides an alternative method for identifying demand trends.

We developed a spreadsheet-based leading-indicator engine and used it to analyze a data set that covers 26 months and includes some 3,500 semiconductor products from eight business units. We found that the leading-indicator engine often can find indicators that predict group demand patterns one to seven months ahead of time with correlations of 0.51 to 0.95. Moreover, these leading indicators can produce reliable forecasts for the product groups.

Empirical Analysis

The leading-indicator engine analyzes the data for a group of products, systematically searches for leading-indicator products for the group, and forecasts demand based on the leading indicators identified (appendix). The tool also can be used in a scenario-analysis mode to test whether a particular product is a strong leading indicator for a group of products. For all of our experiments, we used an estimation-validation procedure: we designate, say, the first 15 months in the data set as the estimation-period (EP) data, the historical demand data used to generate the forecast. We reserve the remaining

![Figure 2: The left chart shows a leading indicator that predicts the demand pattern of a larger group three months ahead of time with a correlation of 0.95. The right chart shows a leading indicator that predicts the demand pattern of a larger group six months ahead of time with a correlation of 0.82. In these examples, the demand of the leading indicator product was less than two percent of the group’s demand and was excluded from the cluster’s demand.](http://www.example.com/figure2.png)
11 months as the validation period (VP) data, the historical demand data against which the forecast is evaluated and the forecast error is calculated. We calculate the forecast error using mean absolute percentage error (MAPE).

Identifying Leading Indicators and Developing Forecasts
For a cluster of 643 products in one business unit, we first performed the leading-indicator analysis with an EP covering months 1 through 15 and a VP covering months 16 through 26. We evaluated each of the 643 products for time-lag values from one to seven months. We calculated the correlation between the product’s demand series offset by the time lag and the cluster’s demand excluding the product under consideration (Figure 3(a)). We then ranked all of the product-time-lag pairs by their absolute correlation values over the EP. For the top 100 product-time-lag pairs (leading indicators), each with absolute correlation values above 0.6, we produced a leading-indicator-based forecast for months 16 through 26. We computed the forecasting error (in MAPE) using the actual shipment data from the VP. Thirty-four products had MAPE values of at most 20 percent for the one-month forecast (month 16), and 28 products had MAPE values of at most 40 percent for the 11-month forecast (months 16 to 26). The results suggest that a pool of strong leading indicators exists for products in this business unit (Table 1).

Many leading indicators had time lags longer than four months, suggesting that they can forecast changes in demand far enough in advance to reserve capacity. Some of the products with long time lags performed well in forecasting while others performed poorly (Figure 4). One reason why products with the longer time lags may perform poorly is that we have fewer data points available for the correlation analysis after we shift the data to account for the time lag. We also found that a strong correlation value alone is not a sufficient measure for determining a leading indicator; in several instances, products with relatively lower absolute correlation values produce good forecasts.

Incorporating New Information
As new information becomes available, an indicator’s correlation value and forecasting performance are likely to change. We need mechanisms to update leading-indicator products and to determine how much historical data to use. To gain insight into updating, we performed the leading-indicator analysis for a second time horizon. We considered an EP covering months 1 through 20 and a VP covering months 21 through 26 (Figure 3(b)). Then we compared the leading-indicator products identified using this EP to those identified for the EP of months 1 through 15. Of the top 100 leading indicators previously identified, 40 are on the list of the top 50 leading indicators for the new EP. This result indicates that the set of 100 potential leading indicators includes leading indicators that remain strong with the new information and leading indicators that mislead and should be disregarded.

To determine how much historical data to use, we performed the leading-indicator analysis for a third time horizon using an EP of months 6 through 20 and a VP of months 21 through 26 (Figure 3(c)). We compared these leading indicators to those for the second EP. Of the top 50 leading indicators for the second EP (months 1 through 20), 25 are on the list of the top 50 leading indicators for the third EP (months 6 through 20). Therefore, we cannot conclude that more recent data leads to better performance. Using the longer estimation period (months 1 through 20) requires more data but identifies leading indicators that perform well over a longer time horizon. Using the shorter estimation period, however, permits us to identify as potential leading indicators products that initially performed poorly but perform well based on more recent data.

To forecast the capacity requirement of a particular wafer-fab process, we next restricted our leading-indicator analysis to a subcluster with 120 products that require the same wafer fab. We performed the leading indicator analysis for an EP of months 1 through 20 and a VP of months 21 through 26. We obtained 10 potential leading indicators with absolute correlation values above 0.5. The average MAPE value for these products is 25 percent for the one-month forecast horizon and 40 percent for the six-month forecast horizon. The product with the highest absolute correlation value (0.668) provides a signal for the demand pattern of the cluster two months ahead (Figure 5). The forecast generated from this leading
Figure 3: Each chart shows the forecasting performance of one leading indicator for a pair of estimation and validation periods. The charts on the left side show the actual data of the leading-indicator product (with the quantity on the left axis) and the data of the cluster (with the quantity on the right axis). The time series of the cluster is shifted ahead by the appropriate time lag to show the mapping between the two patterns. The charts on the right side show the demand of the cluster and the forecast generated from the leading indicator. The vertical line separates the estimation period from the validation period. The first leading indicator provides a signal for the demand pattern of the cluster seven months ahead of time with a correlation of 0.625 and results in 20.11 percent forecasting MAPE over the 11-month validation period.
indicator has a small MAPE of 13.76 percent during the six-month VP. Another product performs in a similar way but, unlike the first, is not among the top 50 indicators for the entire cluster. This shows that there is no reason to believe that a strong leading indicator for a subgroup is necessarily a good indicator for the wider group.

**Testing for Seasonality**

To find out whether seasonality plays a role in the leading-indicator analysis, we first verified its presence in the data set using Fisher’s Kappa test and Barlett’s Kolmogorov-Smirnov test (Fuller 1996). The latter allows for small sample sizes (<100) and compares the normalized cumulative periodogram with the cumulative distribution function of the uniform (0, 1) to test the null hypothesis that the series is white noise (Miller 1956). With 95 percent confidence, we could not reject the null hypothesis that the data set does not demonstrate seasonality.

**Evaluating Intuitive Leading Indicators**

Many supply-demand planners believe in intuitive leading indicators, products whose characteristics suggest that they are natural leading indicators for a group of products. From a business perspective, this idea is appealing. Managers may keep track of an important customer’s high-volume, revenue-driving product and want to know if this product is a leading indicator for a group of related products. We can use the leading-indicator engine to evaluate whether an individual product or a composite product is a strong leading indicator. With a composite product, we can consider successive generations of a technology collectively as a potential leading indicator.

For our data set, we created a composite product from 12 products. The 12 products accounted for about 15 percent of the total volume sold by the business entity (Figure 6). To determine whether the 12-product composite product was a leading indicator, we performed the leading-indicator analysis over two time horizons; the first has an EP of months 9 through 24 and the second an EP of months 14 through 24. In both cases, we used months 25 and 26 as the VP. We considered a time lag of zero to compare the concurrent demand patterns of the composite product (CP) and the cluster (Figure 7, Table 2), which are similar. For time lags greater than zero, the forecast errors for the VP are generally low, indicating that the composite product is a strong leading indicator for the cluster.

Next, we determined whether the CP was a leading indicator for the products in the business entity.

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Table 1: The top 100 leading indicators are grouped by their MAPE values for the one-month forecast (month 16) and the 11-month forecast (months 16 to 26) and by their time lags.

<table>
<thead>
<tr>
<th>MAPE (%)</th>
<th>Time lag</th>
<th>One-month total</th>
<th>Time lag</th>
<th>11-month total</th>
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<td></td>
<td>1, 2, or 3</td>
<td>4 or 5</td>
<td>6 or 7</td>
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<td>0-20</td>
<td>5</td>
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Figure 4: This plot summarizes the 11-month forecasting performance of the top 100 demand leading indicators characterized by time lag and absolute value of correlation.
that share the same fab capacity. Seven of the 12 products in the CP require the same fab process and thus share the capacity. To keep the example simple, we restricted our attention to these seven and created a modified CP (CP2). Within the business entity, 74 products share the same fab capacity with CP2, and the products in CP2 constitute approximately 22 percent of the total volume. Shipments for the composite CP2 occur in months 14 through 26. Therefore, we performed the leading-indicator analysis with an EP of months 14 to 24 and a VP of months 25 and 26. Because large time-lag values result in a small number of data points for the correlation calculations, we restricted the time lags to values from one to four to avoid misleading correlation values.

CP2 performed well as a leading indicator for the subcluster with respect to the correlation values and the MAPE values (Table 3). However, the original CP, which includes products outside the subcluster, performed poorly as a leading indicator. This example

Estimation period: month 1 to 20, validation period: month 21 to 26
(a) leading indicator: time lag = 2, correlation = 0.668, 6-month forecast: MAPE = 13.76%

(b) Leading indicator: time lag = 5, correlation = 0.651, 6-month forecast: MAPE = 19.50%

Figure 5: These charts show the forecasting performances of two leading indicators for a subcluster of products that share the same wafer-fab process. The leading indicator in the top charts has the highest absolute correlation value and is among the top 50 leading indicators for the entire cluster.

Figure 6: Each solid line shows the monthly shipment quantity of one product included in a 12-product composite product. The dashed line shows the monthly shipment quantity of the composite product.
suggests that identifying a leading indicator does not happen by accident and that, by choosing a correct leading indicator, we can obtain advanced demand signals needed for capacity planning.

The Effect of Seasonality

The data we used in our experiments concerns a family of mass storage devices with fairly stable, potentially cyclic demand. To determine whether seasonality plays a role in the leading-indicator analysis, we applied Barlett’s Kolmogorov-Smirnov test (Miller 1956), with 95 percent confidence, and we detected seasonality. Upon inspection, we determined that seasonality repeats quarterly. To study its effect, we deseasonalized the data using Winter’s method (Silver et al. 1998) assuming a three-month cycle. Then we repeated the leading-indicator analysis and compared the forecasting performance (MAPE) of the leading indicator (Table 4).

While deseasonalization creates a better fit during the EP, it produces overall worse forecasting performance. Other studies show similar intuitive results for economic leading indicators (Neftci 1979, Wells 1999). One possible reason may be the difficulty in eliminating seasonal fluctuations without distorting the rest of the information in the data. By adjusting seasonality, we may remove characteristics in the demand information that we want to capture with the leading indicator.

Capacity Planning and Negotiation

For Agere, the leading-indicator analysis provides a new perspective on demand forecasting and a tool to support capacity planning and negotiation. The leading indicators predict the demand patterns for broader product groups. In the context of capacity planning, we grouped products by technology or manufacturing resources because the predicted aggregate demand corresponds directly to future capacity requirements.

Configuring and allocating capacity are crucial in semiconductor firms for several reasons. First, equipment procurement and clean-room construction are very costly and time consuming. Although outside foundries own much of the capacity, state-of-the-art manufacturing equipment often costs millions of dol-

![Figure 7: From top to bottom, the chart shows the monthly shipment quantity of the cluster including the composite product, the cluster excluding the composite product, and the composite product.](image)

<table>
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<tr>
<th>Time lag (VP: 25, 26)</th>
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<th>MAPE (%)</th>
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Table 3: We show the forecasting performance of a 12-product composite product (CP) and a modified composite product (CP2). For the subcluster of 74 products that share the same wafer-fab process as CP2, it performs better as a leading indicator than CP does.

Table 4: We compared the forecasting performance of the composite product as a leading indicator for the original data and the deseasonalized data. The entries show the difference in MAPE between the original and the deseasonalized values. A negative number signifies that deseasonalization produces an improvement.

Conclusions and Future Directions
We have identified products that provide advanced warning of demand changes and that produce reliable demand forecasts. In addition to capacity planning and negotiation, we can extend the leading indicator concept to other corporate planning functions.
Financial Forecasting
The leading-indicator approach can be used to project revenue for a fiscal period based on the trends in revenue streams. For financially critical product groups, analysts can develop leading indicators to predict potential revenue shortfalls or new business opportunities. However, capacity planning and revenue forecasting differ in the data that drives planning. Planning capacity concerns expected requirements for resources, whereas forecasting revenue concerns estimated sales for a market segment, business entity, or customer. To reflect this difference, analysts can define demand in terms of sales rather than unit volume.

Inventory Forecasting
The leading-indicator approach can also be used to project inventory cost or inventory velocity for a future period. Inventory is difficult to project in the high-tech industry because it is a product of such volatile factors as sales, product mix, product cost, manufacturing yield, cycle-time variation, and supply volatility. A method to simplify forecasting inventory will be valuable. The leading indicators we studied are based on characterizing demand. Because inventory is driven by many factors, our analysis has limited applicability to predicting inventory. However, researchers can conduct a similar analysis based on identifying leading indicators for inventory cost, or they can develop leading indicators for each of the factors that influences inventory and combine them to derive a leading indicator for inventory.

Predicting Demand Growth
Each semiconductor product goes through only one life cycle of growth, stability, and decline. Therefore, we can express the cumulative demand for a product over its life cycle as an S-shaped function. The shape of this function specifies the precise pattern of demand growth over time. More specifically, the point of inflection of an S-shaped function, which represents the most drastic change, characterizes the demand growth pattern. We are currently examining statistical methods that use the leading indicator products to streamline the projection of demand growth patterns.

For a product group, we can probabilistically project a number of demand growth patterns from the current point in time to the end of the demand life cycle. However, the variance associated with such projections can be so high that they may not be useful (Figure 8(a)). Using the leading indicator, we can (Bayesian) update the initial demand projections and reduce the associated variance (Figure 8b). The reduction in variance can be significant because a small movement on the time axis might correspond to a drastic change on the demand curve, especially when the point of inflection of the growth curves is included in the movement.

Technology Substitutions
In forecasting technology and characterizing demand, an additional complication is the replacement effect demonstrated by subsequent generations of a technology. For example, at some time during the life cycle of a chip designed for a cell-phone model, the firm will be developing a next-generation chip, perhaps for a new cell-phone model. The demands for the new product will begin to replace the demands for the old

![Figure 8](image_url)

Figure 8: The charts show the variation in the projected demand scenarios for a product based on five months of data when there is no leading indicator (a) and when there is a leading indicator (b). We can use the additional information from the leading-indicator products to update the initial projections of the growth models and reduce the variance.
product during its life cycle. The migration of technology innovation over multiple generations may not be clean cut and may include overlaps, driven by a complex replacement relationship (for example, one new chip may replace several existing chips). Researchers (Sharif and Kabir 1976, Kumar and Kumar 1992, Islam and Meade 1997) have proposed simplified technological substitution models to capture the successive generations of technology products. We are extending our analysis of leading indicators to examine the implications of technology substitution.

Appendix

The Leading-Indicator Search Procedure

1. We identify a product group of interest and set a threshold specifying the minimum time lag (k), maximum time lag (k'), and correlation. To initialize the procedure, we group all the products into one cluster.

2. To find all the leading indicators above the required threshold, for each product i in a given cluster C,
   (a) we set time lag k = k,
   (b) we compute the correlation between the demand time series associated with product i where the time series is offset by k and the demand time series associated with the cluster excluding product i (set C\{i}),
   (c) we record the correlation number \( \rho_{ik} \) computed for product i and time lag k, we set k = k + 1, and if k \( \leq k' \), we repeat Step (b).

3. We examine all the recorded correlation numbers \( \rho_{ik} \). If at least one of the correlation values \( \rho_{ik} \) and its corresponding time lag k satisfy the specified threshold, we go to Step 4. Otherwise, we recluster as follows:
   (a) Using statistical cluster analysis, we subdivide the product group into clusters based on statistical patterns in each product’s historical demand; we may use various attributes for clustering, for example, mean shipment quantity, shipment frequency, volatility, or skewness.
   (b) We repeat Steps 2 and 3 for each cluster.

4. We return the leading indicator(s) and the corresponding product cluster(s).

Experimental Settings and Procedures

We let [1, T] be the time period (in months) for which the shipment data is available. We split the T-month data set into an estimation period (EP) and a validation period (VP). We use the subperiod \([t_0, t_1]\) as the EP in which we identify the leading indicators and determine the parameters for the forecast. We use the remaining time period \([t_1 + 1, T]\) as the VP over which we evaluate the forecasting performance of a potential leading indicator. We can validate any \( h \)-month forecast by comparing the forecast to actual shipments, \( h \in [1, T - t_1] \).

Measuring Forecast Error Using Available Shipment Data

Throughout the experiments, we calculated the mean absolute percentage error (MAPE) as follows:

\[
\text{MAPE}(\hat{Y}) = \frac{1}{T} \sum_{t=1}^{T} \left| \frac{y_t - \hat{y}_t}{y_t} \right|, \tag{1}
\]

where \( y_t \) is the actual shipment quantity during period \( t \) and \( \hat{y}_t \) is the shipment quantity estimated by the trend line during period \( t \). During the EP, we first generated a trend line to fit the data, and we calculated the MAPE to measure how well a particular trend line fits the data. In the VP, we calculated the MAPE to measure how well the trend line predicts the demand as a percentage of the actual (shipment) quantity.

The Coefficient of Correlation

Over the estimation period \([t_0, t_1]\), we quantified the degree of the linear relationship between the time series of cluster C and product i at time lag k by calculating the following correlation coefficient:

\[
\rho_{ik} = \frac{\sum_{t=t_0+k}^{t_0+k+k}(x_{i,t-k} - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=t_0+k}^{t_0+k+k}(x_{i,t-k} - \bar{x})^2} \sum_{t=t_0+k}^{t_0+k+k}(y_t - \bar{y})^2}, \tag{2}
\]

where \( x_{i,t} \) and \( y_t \) denote the actual shipment quantities of a potential leading indicator \( i \), and the rest of the cluster in month \( t \), and \( \bar{x} \) and \( \bar{y} \) are the average shipment quantities over the time horizons for which we calculated correlation. Thus, the correlation coefficient \( \rho_{ik} \) measures how well the demand of item \( i \) over time period \([t_0, t_0+k]\) predicts the demand of the cluster over \([t_0+k, t_1]\).

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We determined the correlation coefficient by comparing the time series of the item against that of the rest of the cluster. We adjusted the total shipment quantity of the cluster by removing the item's quantity from each month's shipment quantity. In this way, we eliminated the bias that might be introduced from a (high-volume) dominating item.

The Leading-Indicator-Based Forecast

After we identified a leading indicator \( i \) from a cluster \( C \) based on time lag \( k \) and coefficient of correlation \( \rho_{ik} \), we constructed a forecast for cluster \( C \) based on the time series of the leading indicator using the following procedure:

1. We regressed the time series of cluster \( C \) over \([t_0 + k, t_1]\) against the time series of the leading indicator over \([t_0, t_1 - k]\). We determined the corresponding regression parameters \( \hat{\beta}_0 \) and \( \hat{\beta}_1 \).

2. For a given month \( t \), we generated the forecast for the cluster, \( \hat{y}_i \), using \( k \)-month earlier time-series data of the leading indicator \( i \) as follows:

\[
\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i,t-k}.
\]

3. We calculated the fitting error over the estimation period \([t_0, t_1]\) as MAPE\((m)\) for \( m = t_1 - t_0 + 1 - k \).

4. We calculated the forecast error over the validation period, \([t_1 + 1, T]\) as MAPE\((h)\) based on (1) for an \( h \)-month forecast.

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