New Product Forecasting in Volatile Markets

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Summary: Forecasting demand for limited-life cycle products is essentially projecting an arc trend of demand growth and decline over a relatively short time horizon. For products with stable market shares, forecasting demand over the life cycle benefits from the high degree of correlation with prior sales of similar products. But for volatile-share markets, rapid innovation continually alters the shape of available features and performance, leading to products with demand patterns that differ greatly from prior generations and forecasting techniques that rely more on judgment and naïve expectations. We hypothesized certain characteristics about the shape and volatility of the demand trend in volatile-market product, and tested them using sample data from a partner firm. We found significant differences in quantifiable characteristics such as skew and variance over the life cycle, presenting an opportunity for supply chain stakeholders to incorporate life cycle effects into forecasting models.

Introduction
Imagine that your company is introducing an innovative new durable product to market. You have been involved in this market for more than a decade, with a stable, leading position relative to the competition where you have a large degree of influence on product technology and trends. Products in this market have a lifespan of five or more years, and technological changes are evolutionary rather than revolutionary. In such a stable market, forecasting and managing product demand is a relatively straightforward task, with gradual changes in demand trends and historical sales data accurately predicts future demand. On the other hand, consider introducing an innovative durable product into a more volatile market where product life cycles are shorter, technological changes are revolutionary, and as a result each firm’s share of the market varies greatly between product generations as consumers polarize around feature sets in a manner that is difficult to predict.

KEY INSIGHTS
1. Stability in market share quantifiably influences the trend in product demand for durable products
2. The product life cycle can be quantified in distinct phases of growth and decline
3. Conjoint methods that measure influence of volatility over the life cycle can improve accuracy

Figure 1: Research Objective
How many products do you need to produce in this sort of market? Many important decisions will be made as a result of your forecast: new capital investments will be made in a factory for the new technology, a sales channel will be created to attract new customers, and your distribution network will have to be modified to deliver the product to those customers. If your product is successful, you will need to quickly add capacity along the supply chain. If your product is not successful, you will need to sunset the product in order to free capital resources to focus on the next generation of the product or other markets.

**Stable and Volatile Markets**

Many supply chain models are based on assumptions of relative stability in market share. For instance, econometric forecasting models use historical sales data for a certain product to predict its future demand. This approach relies on the implicit assumption that the future demand will exhibit the same pattern(s) observed in the past — an approach that does not work for limited-life cycle products whose features and performance evolve quickly, with a resulting volatile reception from the market.

Where pure statistical models fail, forecasters use judgment analysis to create demand forecasts. A review of the literature and a case study with a partner firm revealed sentiment that even with modern computer-aided forecasting techniques, new product forecasting in volatile markets relies too heavily on judgment. This was echoed by supply chain professionals in disciplines ranging from capacity planning to transportation to inventory management — all of whom play key roles in a firm’s Sales and Operations Planning (S&OP) processes and are thus impacted by the accuracy of demand forecasting.

We were motivated to explore how firms might improve their insight into trends in product demand for volatile markets using intrinsic, rule-based demand trend analysis, as opposed to econometric models that suffer from the negative effects described above. To do this, we hypothesized how volatility in market shares might affect the demand line with the effects of the *product life cycle* at the top of mind.

**Quantifying the Demand Trend**

There are limitless statistics that can be used to describe the distribution of sales volume over time. Our choice of statistics was shaped by three key supply chain disciplines:

- **Sales forecasting**, which is primarily concerned with financial results
- **Capacity planning**, which is concerned with making human and capital resources available to produce and transport products.
- **Inventory management**, which is concerned with setting inventory stocks throughout the supply chain.

Taking these roles as primary stakeholders, we considered what aspects of the demand trend impact their key decisions, ultimately choosing four metrics:

- **Rate of Growth/Decline**, which determines how quickly the supply chain must react to changes in demand.
- **Skew**, which influences whether the supply chain should be tailored to an earlier or later peak in demand, and for how long it must support the tail ends.
- **Variation**, which influences the level of supply buffers used in the supply chain.
- **Modality**, which brings a requirement for variable output in production over time.

Using these metrics, we designed an experiment that could be performed to test their relevance over different phases of the product life cycle. For each metric, we formed a hypothesis about the effects of volatility: volatile products were assumed to have faster rates of growth/decline, right-hand skew, higher variation, and multi-modal sales trends. Using sample sales or shipment data, these statistics would then be pooled for stable and volatile markets, and their differences would be compared for statistical significance.

**Case Study**

We partnered with a firm that produces a range of durable, limited-life products in both stable and volatile markets, with frequent new product introductions. We began with monthly shipment data for a range of products, and ultimately selected four volatile-market products and eight stable-market
products for our sample groups. Each product had a complete or nearly-complete life cycle incorporating 2-4 years of data, and all products were free from exogenous shocks to the demand trend.

The results of our study empirically confirmed our hypothesis for rate of growth/decline, skew, and variation. Due to a relatively small sample size and few initial assumptions about time series data (i.e. normality), we used permutation testing – where samples are regrouped and means calculated in multiple iterations – to establish a plausible level of statistical significance. De-trended data was used where appropriate.

Our results for modality were less conclusive. We utilized a statistical dip test – which measures length and depth of a drop between maxima – to test for multi-modality in the volatile products. The results of this test yielded low statistical significance, although some products’ trend lines presented visual indication.

### Table 1: Summary of Results

<table>
<thead>
<tr>
<th>Measure</th>
<th>Volatility Influence</th>
<th>Empirical Result</th>
<th>Statistical Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Skew</td>
<td>Greater Right Skew</td>
<td>Confirmed</td>
<td>Medium</td>
</tr>
<tr>
<td>Rate</td>
<td>Greater Rate</td>
<td>Confirmed</td>
<td>Low</td>
</tr>
<tr>
<td>Variance</td>
<td>Greater Variance</td>
<td>Confirmed</td>
<td>Low</td>
</tr>
<tr>
<td>Modality</td>
<td>Multi-Modal</td>
<td>Inconclusive</td>
<td>None</td>
</tr>
</tbody>
</table>

### Implications

Using the lenses of sales forecasting, capacity planning, and inventory management, we examined the implications of volatility-influenced demand trends:

**Skew** was right-handed for volatile-market products, as expected. For *sales forecasters*, skew implies the existence of a long tail in demand later in the life cycle with an associated revenue stream. This poses a challenge for *capacity planners*, as smaller economies of scale are in play, requiring a production system that is more flexible in terms of output. If this is not the case, we would expect to see volatile market products ceasing production sooner after the peak, as the tail is less profitable.

**Rates of Growth and Decline** were found to be steeper for volatile products. This is important to *capacity planners* in volatile markets who must design their systems to ramp up quickly, amidst frequent new product introductions. It also influences *sales forecasters* because the revenue streams for each product are concentrated into fewer accounting periods, and *inventory managers* because the proportional level of safety stocks will change rapidly over just a few months’ time.

**Variance** is an important consideration for *inventory management*, which must use inventory stocks to buffer for variance in production and distribution processes. Volatile markets were found to have higher variance, which drives a profitability conversation with between with *sales forecasters* on the relative costs of higher inventory stocks.

**Modality** is an important consideration for *capacity planners*, who must decide on how to handle lower-order-of-magnitude production output during dips between modes. Just as with rates of growth/decline, a decision must be made about whether to alter output or carry inventory.

### Potential Application

These insights have the potential for application in *conjoint forecasting*, which fuses quantitative and judgment analysis in an informed approach. Simple yet effective rule-based forecasting processes can be established, for instance, the known rate of growth/decline during the introductory phases of a new product can be expressed as a confidence range, against which the actual trend is plotted. A breakout from the confidence range signals a judgment-influenced uptrend in the forecast using the actual shipment trend as the new forecast. This is just one many ways that econometrics and judgment can be combined to improve forecast accuracy.