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BRIDGING SHORT AND MID-TERM DEMAND FORECASTING IN THE SEMICONDUCTOR INDUSTRY

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ABSTRACT

Demand planning in the semiconductor industry is typically divided into different planning horizons, mid-term and short-term. Accurate demand forecasting is crucial because of long capacity installation times, long lead-times, short product life cycles, and constantly new technological advances. As demand forecasting for short and mid-term horizons are often made on different product and time granularities using different planning tools, we may see demand fluctuations (on the same granularity) within individual horizons and at the intersections of different granularities. This paper discusses stability of demand forecasts depending on time and product granularity and introduces definitions of good and bad stability, using *Symmetric Mean Absolute Percentage Error* (*SMAPE*) as a measure for stability. We show that time and product granularities have a significant effect on the intra-horizon stability of a demand plan and that planning on different granularities can lead to artificial demand fluctuations at the intersections of planning horizons.

1 INTRODUCTION

Demand forecasting in the semiconductor industry faces several challenges. Due to innovative changes in technology and products, the product life cycle is short but the cycle time to produce the products is intrinsically long. Additionally, capacity installation times are long, and the tool costs are high (Swaminathan 2000). Other factors that make accurate demand planning crucial are complex product flows, random yields, long lead-times, and many uncertainty factors such as technology, market, and customer demand (Hughes and Shott 1986, Huh and Roundy 2005).

In order to overcome these challenges, the bridging of different planning horizons has to be well coordinated. The planning landscape of the semiconductor company of choice is depicted in Figure 1. The company uses a two-stage planning horizon: mid-term tactical planning (*Business Scenario*) and short-term operational planning (*Production Program*). The planning landscape is divided into five planning processes. The focus of this paper is on demand planning. In *Business Scenario*, demand planning is done on an aggregated level to prepare necessary capacity expansions and transfers of technology for month six to month 18. *Production Program* provides a detailed demand plan for the next 26 weeks on fine product and time granularity levels. Stock planning also belongs to the demand planning process but is not considered in this paper. In capacity planning, supply chain recourses are identified and assessed in order to identify capacity constraints which are used for the demand supply match in supply planning. The available capacity is matched against the requested demand from the demand planning and necessary production requests and orders are generated. Production management is the interface to the production sites and its main purposes are to define weekly production requests, to balance production between sites, and to secure minimum stock levels and customer deliveries. Order management is the interface to the customer and confirms orders based on the supply plan.

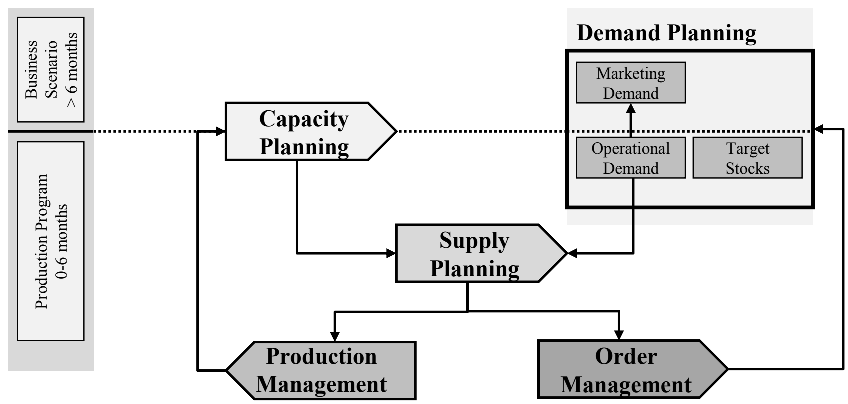

Figure 1: Planning landscape of the company of choice with focus on demand planning.

An important parameter in demand planning is the level of aggregation for each planning horizon, in terms of time buckets, set of items, and set of locations (Zotteri and Kalchschmidt 2007). The choice of the appropriate granularity level depends on the required information and time horizon of the underlying decision-making process (Zotteri, Kalchschmidt, and Caniato 2005). The purpose of aggregation is to reduce demand uncertainty, computational effort, and cost (Caplin 1985, Gelders and van Wassenhove 1982).

A significant problem of aggregation and disaggregation is that a plan which is feasible at a coarse level may not be feasible on a finer granularity (Axsäter 1986). Furthermore, planning on different horizons using different granularities and various tools can lead to a high demand discrepancy at the intersections of these planning horizons. These artificial fluctuations imply volatility and therefore low stability. Hence, the granularity level on which a forecast is made has a considerable impact on the stability of the demand plan. Especially in volatile industries like semiconductor manufacturing, the aim of forecasting is not to choose the granularity that minimizes the fluctuations of the demand plan but to identify and eliminate artificial fluctuations. Therefore, we differentiate between good and bad stability.

In this paper, we introduce definitions of good and bad stability. For that purpose, we develop a systematic framework for the classification of stability depending on time and product granularity. We apply a measure for stability based on the *Symmetric Mean Absolute Percentage Error* (*SMAPE 3*) to a case study of the analyzed semiconductor company. We show that time and product granularities have a significant effect on the stability of a demand plan and analyze whether inter-horizon fluctuations are higher than intra-horizon fluctuations.

The rest of the paper is organized as follows. Section 2 presents the literature review focusing on aggregation and disaggregation and on performance measures in demand planning. In Section 3, we present the stability framework to assess and classify stability, followed by definitions of good and bad stability. The statistical analysis of our case study is described in Section 4. The paper concludes with a summary of the results and recommendations for further research.

2 LITERATURE REVIEW AND RESEARCH BACKGROUND

2.1 Aggregation and Disaggregation in Demand Planning

In hierarchical production planning, each planning level is defined by a specific level of aggregation (Bitran and Hax 1977). One part of the literature on aggregation in forecasting addresses subsequent aggregation and disaggregation of the data. The data is aggregated to an appropriate level, a forecast is made based on this aggregated data, and it is then disaggregated back to the original level. This kind of aggregation is discussed in many publications, for example in Weiss (1984), Gonzalez (1992), and Chan (1993). Axsäter and Jönsson (1984) show that the hierarchical planning approach performs significantly better than non-hierarchical planning in terms of total costs. The authors introduce and evaluate different aggregation and disaggregation procedures. Rogers et al. (1991) develop a framework for aggregation and disaggregation methodologies.

Several authors compare the top-down to the bottom-up approach (Dangerfield and Morris 1992). In the top-down approach, forecasts are made on an aggregate level and are disaggregated to an item level. In the bottom-up approach, forecast are made on an item level and then aggregated. Dangerfield and Morris (1992) conclude that in most situations, the bottom-up approach produces more accurate forecasts.

However, many companies use both aggregation and disaggregation approaches for different decision-making processes. Zotteri, Kalchschmidt, and Caniato (2005) emphasize that forecast accuracy depends on the appropriate choice of the aggregation level and that this issue requires further research. Ott, Heilmayer, and Sng (2013) analyze the effects of product granularity on forecast accuracy and conclude that forecast accuracy increases with coarser product granularities. The coarsest granularity has the highest overall accuracy. Furthermore, the authors analyze the dependency of forecast accuracy over time in a rolling horizon. The shorter the forecast horizon the higher are the forecast accuracies of the product granularities. Most of the above findings in literature have been confirmed over the last years at the semiconductor company of choice. In addition, it was found out, that disaggregation is not always needed. In mid-term and long-term planning, when tactical and strategic decisions are made, planning on an aggregated level is sufficient in terms of planning effort and level of detail of the required information.

2.2 Performance Measures in Demand Planning

In addition to forecast accuracy, other performance measures are important for demand forecasting as well. Yokuma and Armstrong (1995) identify different criteria and analyze their importance for the selection and evaluation of forecasting techniques. The authors name ease of use, ease of interpretation, flexibility, and cost savings of improved decisions as important criteria. Chae (2009) expands the list by forecast volatility. This is also known as forecast stability, plan stability, or inter-plan stability. Generally, inter-plan stability is defined as the amount of difference between two consecutive plans in a rolling horizon procedure (see for example De Kok and Inderfurth 1997, Heisig and Fleischmann 2001). Herrera and Thomas (2010) use the term nervousness for inter-plan stability. In addition, their work is one of the very few which defines instability as the deviations between production quantities of different periods within one plan. This instability is referred to as intra-plan stability hereafter.

The literature review shows that granularities have an impact on forecast accuracy and can lead to stability problems. The literature on performance measures mainly concentrates on forecast accuracy and inter-plan stability. However, the granularity level on which the forecast is made has a significant impact on forecast fluctuations within one plan, and therefore on the intra-plan stability, which has not received much attention in the literature up to now. Demand forecasting for different planning horizons is made on different granularities, and this results in forecast fluctuations at the intersections between horizons, hence within the same granularity level and between different granularities. Consequently, intra-plan stability is an important factor for the choice of an appropriate granularity level and deserves more attention in future research. This paper aims to close this gap by providing a framework for the assessment and classification of stability. We analyze the appropriate level of intra-plan stability and the impact of the granularity level.

3 DISCUSSION OF FORECAST STABILITY

3.1 Framework for Stability

Insufficient coordination and different granularities of the planning horizons can lead to artificial fluctuations within one plan and therefore to an intra-plan stability problem. In order to encounter the different dimensions of volatility, we need to differentiate between good and bad intra-plan stability. For that purpose, we introduce a systematic framework for the assessment and classification of stability. We define three dimensions as depicted in Figure 2. Based on these dimensions, we derive a stability matrix that enables demand planners to investigate the impact of product and time granularities on a specific type of stability and draw conclusions about the appropriate granularity level.

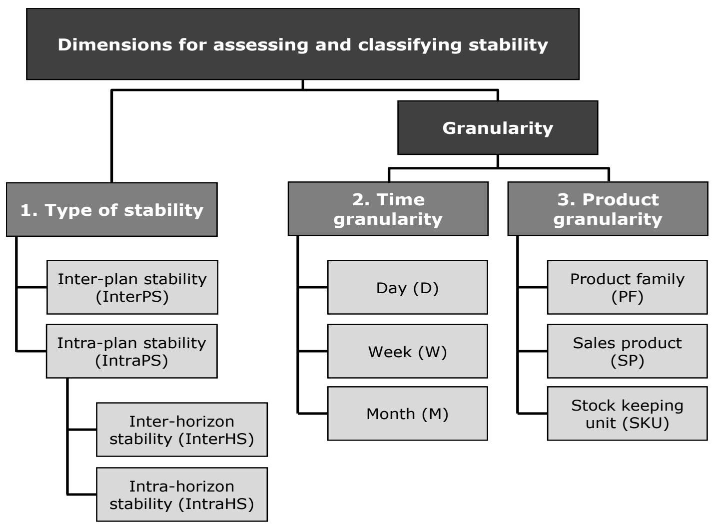

Figure 2: Framework of stability.

As first dimension in our framework, we distinguish several types of stability. Inter-plan stability (**InterPS**) represents the deviations of the same time period from one plan to the next plan as illustrated by the vertical arrows in Figure 3. Intra-plan stability (**IntraPS**) measures the deviations from one period to the next period within one plan. We further classify two different subtypes of intra-plan stability. Inter-horizon stability (**InterHS**) defines the fluctuations at the intersection of different planning horizons (dashed arrows in Figure 3). In contrast, intra-horizon stability (**IntraHS**) measures the volatility within one planning horizon (solid arrows in Figure 3). Furthermore, forecasts can be generated on different aggregation levels, depending on the need of detail of the underlying decision-making process and the available information at the planning point in time. In our stability framework, we differentiate between time and product granularities. Other dimensions like location granularities are possible and could extend the framework. The second dimension covers the impact of time buckets on the stability. In mid-term and short-term demand planning, forecasts are typically made on a daily (**D**), weekly (**W**), or monthly (**M**) basis. The third dimension refers to the product granularity. We narrow the wide field of possible product granularities down to three levels: product family (**PF**), sales product (**SP**), and stock keeping unit (**SKU**). For example, when we consider the product family “power supply”, possible sales products could be *12 V* and *24 V* variants, and stock keeping units represent different manufacturing routes and storage locations. The above mentioned time and product granularities are the most important representatives from our point of view but can be adjusted to the specific use case.

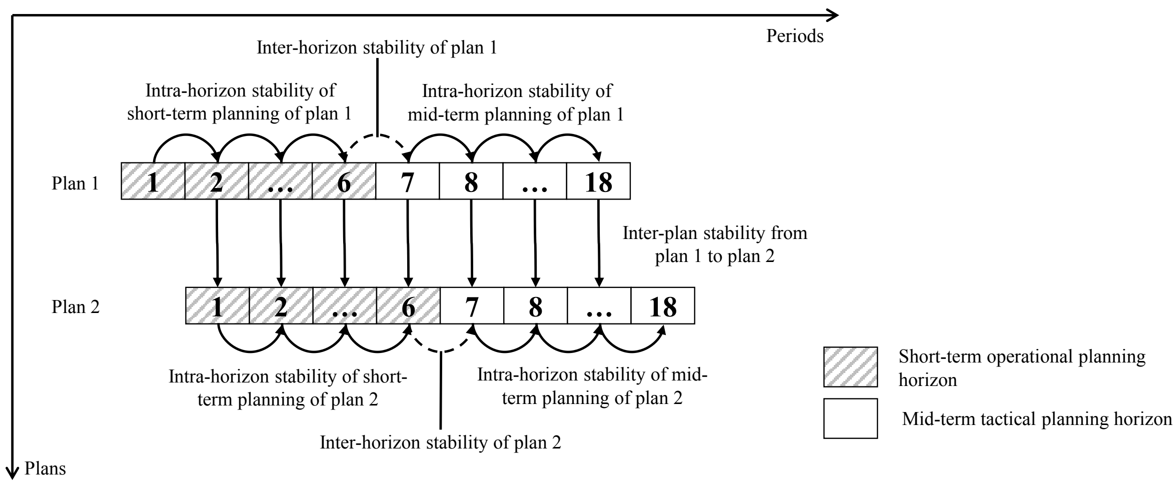

Figure 3: Stability types.

The stability matrix shown in Table 1 summarizes all different combinations. For example, $S_{IntraHS,W,SP}$ represents the intra-horizon stability on weekly time buckets for sales products. In this paper, we focus on intra-plan stability, i.e. inter- and intra-horizon stability. Using this framework, we evaluate the impact of time and product granularity on the forecast stability and draw conclusions about the definition of good and bad stability.

Table 1: Stability matrix.

			Type of Stability		
			InterPS	IntraPS	
			InterPS	InterHS	IntraHS
Granularity	PF	D	$S_{InterPS,D,PF}$	$S_{InterHS,D,PF}$	$S_{IntraHS,D,PF}$
		W	$S_{InterPS,W,PF}$	$S_{InterHS,W,PF}$	$S_{IntraHS,W,PF}$
		M	$S_{InterPS,M,PF}$	$S_{InterHS,M,PF}$	$S_{IntraHS,M,PF}$
	SP	D	$S_{InterPS,D,SP}$	$S_{InterHS,D,SP}$	$S_{IntraHS,D,SP}$
		W	$S_{InterPS,W,SP}$	$S_{InterHS,W,SP}$	$S_{IntraHS,W,SP}$
		M	$S_{InterPS,M,SP}$	$S_{InterHS,M,SP}$	$S_{IntraHS,M,SP}$
	SKU	D	$S_{InterPS,D,SKU}$	$S_{InterHS,D,SKU}$	$S_{IntraHS,D,SKU}$
		W	$S_{InterPS,W,SKU}$	$S_{InterHS,W,SKU}$	$S_{IntraHS,W,SKU}$
		M	$S_{InterPS,M,SKU}$	$S_{InterHS,M,SKU}$	$S_{IntraHS,M,SKU}$

3.2 Definition of Good and Bad Stability

The aim of forecasting is not to choose the granularities that minimize the fluctuations of the demand plan. We therefore have to differentiate between good and bad intra-plan stability. Good intra-plan stability reflects fluctuations of the real customer demand. Bad intra-plan stability results from artificial demand fluctuations that are caused by an inappropriate choice of time and product granularities.

In order to differentiate between good and bad intra-plan stability and to determine the optimal level of good stability, we propose a three-step approach: Step 1: Specification of granularity range; Step 2: Impact on intra-horizon stability; Step 3: Impact on inter-horizon stability. A summary of these steps is visualized in Figure 4.

1. Specification of granularity range

- Specification of minimum and maximum granularities which provide information on the required level of detail for the specific decision-making process
- All granularities outside of this specified range lead to bad stability

2. Impact on intra-horizon stability

- Specification of granularity that minimizes intra-horizon fluctuations
- Maximization of intra-horizon stability

3. Impact on inter-horizon stability

- Investigation of the impact on the inter-horizon fluctuation
- Alignment of the aggregation levels so that the planning horizons are optimally harmonized to one another
- Maximization of inter-horizon stability

Figure 4: Three-step approach to differentiate between good and bad intra-plan stability.

In the first step, the minimum and maximum product granularities have to be specified which provide the information on the required level of detail for the specific decision making process. Forecasts for short-term planning provide more detailed information than for mid-term planning. Hence, the forecast has to be made on a finer granularity level. Another factor that has to be taken into account is the planning effort. For mid-term tactical planning for example, forecasting on the finest granularities would firstly be subject to high uncertainty and secondly, the planning effort would be inappropriate for the scope of the planning horizon. All granularities that are outside of this specified range lead to fluctuations caused by an inappropriate granularity choice and therefore to bad stability. After the minimum and maximum granularity levels have been decided, we use the stability matrix to investigate the impact of time and product granularity on the stability of the forecast within this specified range. It is advisable to choose the granularity that minimizes the intra-horizon fluctuations and therefore maximizes the intra-horizon stability. The production has to be able to meet requested volumes which requires careful capacity planning in advance. Mid-term capacity planning in turn is much easier for stable demand plans. In the third step, we evaluate the impact of time and product granularity on the demand fluctuations at the intersections of different planning horizons. If forecasts on these horizons are made on different granularities, artificial discrepancies can occur and lead to instability at the intersections. The aggregation levels have to be aligned so that the planning horizons are optimally harmonized to one another and the inter-horizon stability is maximized. There might be artificial discrepancies as well that have other reasons apart from granularity, like inherent algorithms in different tools, but they are not further discussed in this paper.

To sum up, the individual granularity levels have to be chosen so that they remain in the range specified in the first step, and that the intra-horizon fluctuations as well as the inter-horizon fluctuations are minimized. These granularity levels lead to the optimal degree of good intra-plan stability.

3.3 Application of SMAPE 3 as Volatility Measure

In order to apply the stability framework on real data and to calculate the impact of granularity levels on the stability, we introduce a stability measure for intra-plan stability based on the *Symmetric Mean Absolute Percentage Error 3* (*SMAPE 3*). Originally, *SMAPE 3* is a measure for forecast accuracy. The basic formula is shown in Equation 1. *SMAPE 3* has several advantages compared to other forecast accuracy measures. Firstly, by summing up forecasts F_t and orders O_t of a period t, *SMAPE 3* eliminates the chance of having zero denominators. Furthermore, compared to the exact average, *SMAPE 3* is less sensitive to outliers and errors caused by small scale data (Jing 2011).

$$SMAPE3 = \frac{\sum_{t=1}^{n} |O_t - F_t|}{\sum_{t=1}^{n} (O_t + F_t)} \tag{1}$$

In this paper, we introduce the *SMAPE 3* formula as a measure for volatility over a planning horizon from period *1* to period *n*. Instead of forecasts and orders, we consider the forecasts of each period F_t and the succeeding period F_{t+1}, as shown in Equation 2. In the numerator, we sum up all absolute deviations from one period to its successor. In the denominator, we calculate the sum of the forecast of all periods and its following period. As we want to measure the impact of both time and product granularity, we extend the formula by a second summation from product *1* to product *m*.

$$Volatility = \frac{\sum_{t=1}^{n-1} \sum_{p=1}^{m} |F_{p,t+1} - F_{p,t}|}{\sum_{t=1}^{n-1} \sum_{p=1}^{m} (F_{p,t+1} + F_{p,t})} \tag{2}$$

In order to introduce a measure for intra-plan stability, we take the complement of the volatility formula. This is reasonable because volatility and stability are inversely related: the higher the volatility, the lower is the stability. Therefore, we establish the formula shown in Equation 3 as a measure for intra-plan stability, depending on time and product granularity.

$$Stability = 1 - Volatility \tag{3}$$

The formulas shown in Equation 2 and 3 are applicable to both intra- and inter-horizon stability. For the latter, we only consider the last period of the short-term planning and the first period of the mid-term planning, instead of the whole planning horizon.

4 CASE STUDY: STATISTICAL ANALYSIS OF DEMAND FLUCTUATIONS

4.1 Design of Experiment

The theory developed in the previous section is applied to a case study provided by the semiconductor company of choice. The demand planning landscape is divided into multiple planning levels. We consider the operational short-term *Production Program* (*PP*) and tactical mid-term *Business Scenario* (*BS*). *PP* provides a detailed plan for the next 26 weeks on a weekly granularity. *BS* covers the time horizon from week 26 (hence month 6) to month 18 on a monthly granularity. The relationship of *PP* and *BS* is shown in Figure 5.

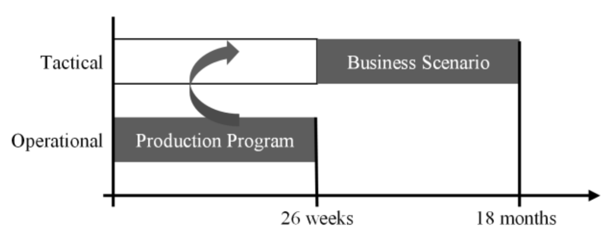

Figure 5: Demand planning horizons of the company of choice.

At the company of choice, a forecast can be made on different product granularities. From coarsest to finest, these are *PPOS*, *RfP*, *SP*, *FP*, and *SKU*. For our case, we choose *RfP*, *SP*, and *SKU* as it can be seen in Figure 6. They correspond to the product granularity levels of the stability framework introduced in Section 3. Forecasts in the mid-term *BS*, which are mainly used to prepare budget decisions regarding capacity investment, are made on *RfP* and coarser granularities. In *PP*, forecasts are available on all product granularities. A higher level forecast can be disaggregated to a lower level forecast by means of defined disaggregation rules.

Figure 6: Overview of granularities.

The statistical analysis is divided into two parts. In the first part, we analyze the *PP* planning horizon in detail and measure the impact of time and product granularities on intra-horizon stability, using the volatility measure developed in Section 3. We use the latest available dataset from the 21st of February 2017. The data set contains demand forecast numbers on weekly time granularity and all product granularities for the next 26 weeks, composed of 6,000 *RfPs*, 7,000 *SPs*, and 13,000 *SKUs*. The weekly forecasts are aggregated in two steps to derive monthly numbers. In the first step, the weekly value is split equally to the seven days of the week. The aggregation from day to month is then the sum of the values from the days belonging to the month. In order to determine the number of days in a specific month, a method similar to the Actual/Actual Method known from day count convention in finance is used in demand planning at the company of choice.

In the second part, we conduct an analysis of the whole planning horizon, including *PP* and *BS*. The aim of this analysis is to investigate whether artificial fluctuations at the intersection of these planning horizons exist and therefore lead to a stability problem. For that purpose, we evaluate whether inter-horizon fluctuations are higher than intra-horizon fluctuations. We use eight quarterly datasets from June 2015 until March 2017. The datasets are composed of the unconstraint demand of *PP* and the uncapped demand of *BS*. Both describe a demand request without considering any capacity constraints and represent the output of the demand forecasting process. The timeframe of each dataset includes five months *PP* and further twelve months *BS*. The data of the first month of *PP* is incomplete because it overlaps with already actual data due to the data extraction logic. Therefore, it is excluded from our analysis. The forecast numbers are on monthly time granularity and *RfP* product granularity.

4.2 Influence of Granularities on Intra-Horizon Stability

Ott, Heilmayer, and Sng (2013) already analyzed the influence of product granularities on forecast accuracy and identified that forecast accuracy increases with coarser product levels. In this paper, we analyze the impact of product and time granularities on forecast intra-horizon stability.

Figure 7 shows the average weekly and monthly volatilities of the three product granularities. We have normalized the *SKU monthly volatility* to 20% to protect the privacy of the company's data.

The bars illustrate that there is a negative correlation between product granularity and volatility: the coarser the product granularity, the lower is the volatility. The coarsest product granularity *RfP* has the lowest overall volatility. This relationship is mathematically explainable. To calculate the intra-horizon volatility, all absolute fluctuations are summed up to derive the overall absolute deviation, i.e. the numerator of the volatility formula. If the intra-horizon volatility is calculated for a coarser product granularity, the information about fluctuations on finer granularities are lost. Therefore, the numerator of the volatility formula on a coarser product granularity is lower or equal compared to the numerator on a finer product granularity. This leads to a lower volatility.

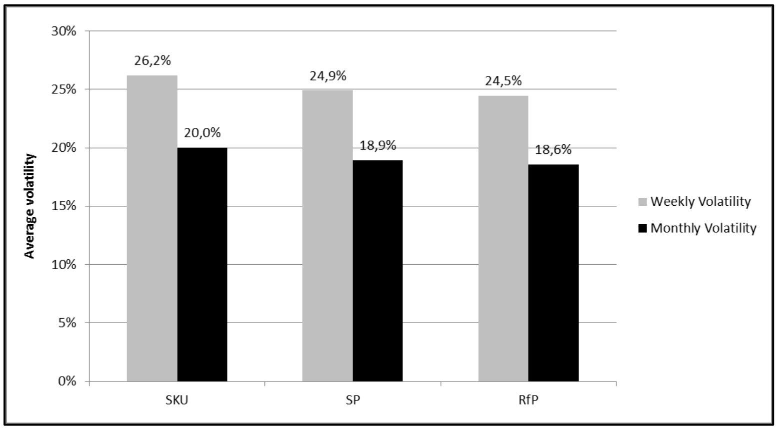

Figure 7: Average weekly and monthly volatility of the product granularities (normalized to *20 % monthly SKU volatility*).

Concerning the relationship between weekly and monthly volatility, the results of Figure 7 show that the weekly volatility is higher than the monthly volatility for all product granularities. Consequently, time aggregation to months smoothens weekly fluctuations in our case. However, we realize that the volatility measured with *SMAPE 3* is influenced by the underlying distribution of the data. We have seen that a trend results in a higher monthly than weekly volatility. Other factors like seasonality may play a role as well, but are not observed in our data sample.

4.3 Analysis of Inter-Horizon Stability

The goal of the second part of the statistical analysis is to verify whether there is a fluctuation at the intersection of *PP* and *BS* that is higher than a normal forecast fluctuation, thus whether there is an artificial inter-horizon fluctuation that is caused by inappropriate planning and alignment of the different planning horizons. Figure 8 depicts the intra-horizon and inter-horizon volatility of *PP* and *BS*, from one month to the next. The fluctuations are average numbers for all eight datasets from June 2015 to March 2017. The first fluctuation of the *PP* horizon is distinctly higher than all other fluctuations because of backlog which has to be depleted.

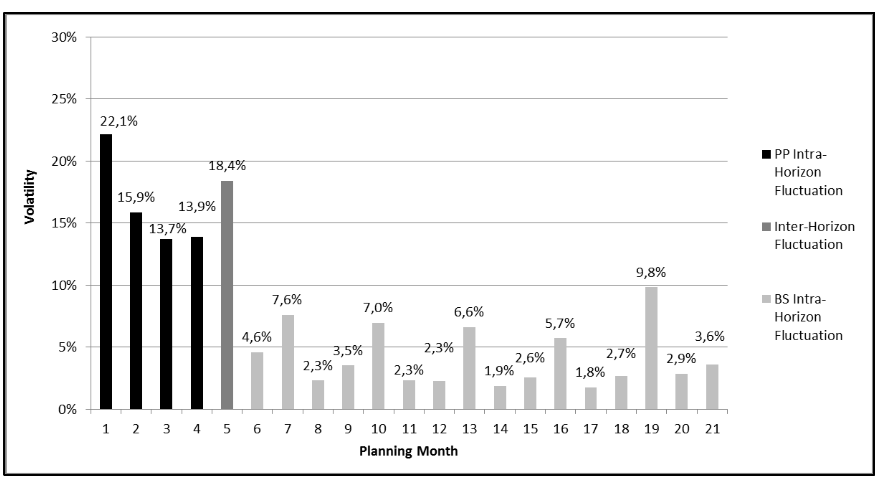

Figure 8: Intra-horizon and inter-horizon fluctuations of *PP* and *BS* planning horizon (average across all datasets; normalized).

We derive three volatility measures. The *PP* intra-horizon volatility reflects the average forecast fluctuation of the five planning periods of *PP*. Analogously, the *BS* intra-horizon volatility reflects the average forecast fluctuation of the twelve planning periods of *BS*. The inter-horizon volatility represents the possibly artificial fluctuation at the intersection of *PP* and *BS*. Using these volatility measures, inter-horizon and intra-horizon volatilities can be compared against one another. We realize that the intra-horizon volatility of *PP* is significantly higher than of *BS*, as it is visualized in Figure 8. The reason is that *PP* forecasts partly rely on real volatile customer demand, whereas *BS* planning merely relies on stable mid-term forecasts. In order to draw a conclusion about the artificiality of the inter-horizon volatility, we compare it to the intra-horizon volatility of the *PP* horizon. Merely, if the inter-horizon fluctuation is higher than an average *PP* intra-horizon fluctuation, a stability problem exists. Figure 9 shows the average intra-horizon and inter-horizon volatility measures of the semiconductor company of choice at three different time periods, i.e. June 2015, March 2016, and December 2016.

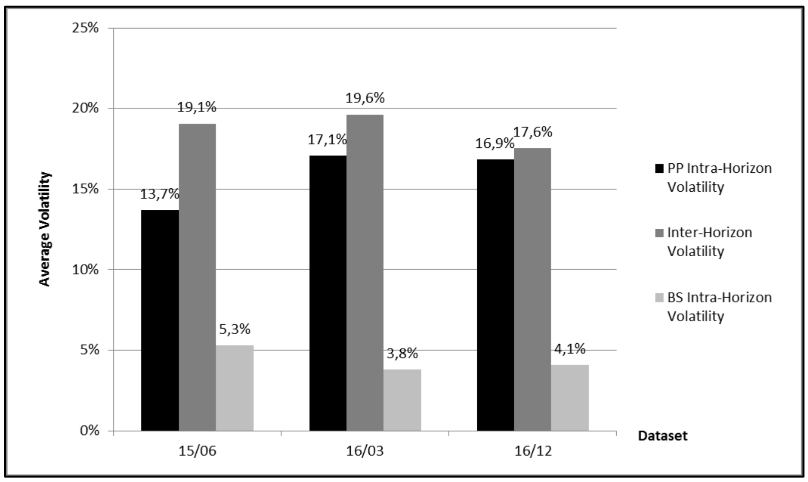

Figure 9: Average intra-horizon and inter-horizon volatility of datasets 15/06, 16/03, and 16/12.

The results of Figure 9 show that, in all three time periods, the inter-horizon volatility is higher than an average intra-horizon fluctuation of the *PP* horizon. We can conclude that the inter-horizon fluctuation is at least partly artificial, caused by inappropriate granularity choices, and therefore, leads to a stability problem at the intersection of the different planning horizons. However, the *PP* intra-horizon and the inter-horizon volatility are converging. In June 2015, the inter-horizon fluctuation is significantly higher than an average *PP* intra-horizon fluctuation, whereas in December 2016, the two measures are nearly on the same level. The results show that the individual forecasting processes and their alignment have significantly improved over the last two years, although the granularities of *PP* and *BS* have not changed. Therefore, the inter-horizon volatility has other reasons as well, apart from the granularity level.

5 CONCLUSION

Demand forecasting in hierarchical planning systems is made on different planning horizons using different levels of product and time aggregation. The literature mainly focuses on inter-plan stability. However, the choice of granularity level also has a significant impact on the fluctuations within one planning horizon. In this paper, we introduced the concept of **intra-plan stability**. For that purpose, we developed a framework for assessing and classifying stability. We defined good and bad intra-plan stability by providing a guideline to differentiate between both types. The *SMAPE 3* formula was applied as a measure for volatility and stability in order to calculate the impact of granularity levels. We applied the stability framework and the volatility measures to real-world data.

The results show that there is a negative correlation between product granularity and volatility, hence the coarser the product granularity the higher the stability. However, additional factors not investigated in this study might have to be taken into consideration in order to give generalizable recommendations for the appropriate product granularity level. Concerning the time granularity, we found that the relationship between weekly and monthly fluctuations depends on the underlying distribution of the forecast data. We identified that *SMAPE 3* generates unintuitive results when comparing the volatilities of different horizon lengths and when facing a trend in the forecast data. This weakness requires improvement in further research.

We observed that, at the company of choice, the inter-horizon volatility has improved over the last years although the granularities have not changed. We conjecture that this is a learning effect over time with the tools and how to handle the intersection. Further research can extend this analysis and confirm these findings or identify underlying causes of inter-horizon fluctuations. A generic approach to quantify good and bad stability could be developed in order to provide a guideline for companies to determine the optimal level of intra-horizon stability for each planning horizon. A further step would be to define the appropriate granularity level of each planning horizon, also taking into account inter-plan stability.

In conclusion, the proposed stability framework and the conducted statistical analysis are a first step towards a systematic measurement of good and bad intra-plan and inter-plan stabilities. We consider this concept as novel and important as it should enable especially semiconductor companies, but also other companies, to investigate and improve the bridging and alignment of their planning horizons and analyze the impact of time and product granularity on intra-horizon and inter-horizon stability.

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