Lancaster Centre For Forecasting

Supply Chain Forecasting: Best Practices & Benchmarking Study

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Contents

Any citation or reference to this publication must include its full reference "M. Weller, S.F. Crone (2012), Supply Chain Forecasting - Best Practices & Benchmark Study, Technical Report 2012-11-01, Lancaster Centre for Forecasting".

1 Executive Summary

This report will provide insights into manufacturer forecasting practice under collaboration and information-sharing (CIS) partnerships within and outside the organisation. It is based on the analysis of 200 responses to an online survey of demand planning professionals from a range of manufacturing companies. The firms range in size from small and mid-sized manufacturers to large multinational enterprises.

The study is intended to fill a gap in research, specifically it will provide a detailed, up-to-date picture of key elements of forecasting practice in the context of today's collaboration-rich environment. This summary will provide an overview of our findings and the conclusions drawn from them. Readers are welcome to contact the authors to discuss any part of the report in more detail.

Summary of Key Findings

High levels of involvement in CIS partnerships

CIS practices are common within the sample. Manufacturers are involved to some extent in S&OP[1] (99% of companies), CPFR[2] (80%), INFO[3] (80%) and VMI[4] (65%). As such, comapnies typically run multiple CIS types in parallel with 85% participating in S&OP in conjunction with at least one of VMI or CPFR. S&OP is also the most heavily practised, firms being more likely to be extremely involved in S&OP than any other form of collaboration. In terms of external collaboration, CPFR is the most intensely practised, followed by less formal data-sharing partnerships (INFO) and VMI the least widely practised.

Range of Internal and External data available to forecasters

Whilst orders and shipments time series data is highly available inside the organisation, other types of information such as promotions and marketing plans are less available. External data is considerably less available in general than internal data and the firms most involved in formal collaboration have more data at their disposal. Sales & order forecasts at the item level and listings/delistings are the most commonly shared types of data, with POS data one of the least available data types.

Information Exchange is often unstructured

Customers share data in a range of ways, the most commonly used methods being relatively unstructured in nature. Email is clearly the most widely used means of communication. Obtaining data through a customer web portal, EDI or collaborative platform are the least common methods. Firms report that data exchange is not consistent between trading partners and differences exist in a range of areas, including the methods of exchange, level of aggregation and types of data exchanged. Companies classified as heavily involved in CPFR report significantly more structure and consistency in their data-sharing partnerships with customers.

Univariate Statistical Methods are commonplace

The simpler univariate class of methods are most widely used in forecasting, led by smoothing, averages and the naive method. They account for 82.1% of all statistical forecasts. Surprisingly, given the amount of additional data available to forecasters, manufacturers indicate that advanced methods capable of leveraging promotional and downstream data are much less widely used (13.5%).

Equal use of Judgement and Statistics

Practitioners report that judgement and statistics feature heavily in their forecasting,

[1]Sales and Operations Planning is defined on page 5
[2]Collaborative Planning, Forecasting and Replenishment is defined on page 5
[3]Other data-sharing partnerships are defined on page 5
[4]Vendor-Managed Inventory is defined on page 5

both separately and in combination. A statistical baseline with judgement applied is the most common (44% of forecasts), followed by statistics only (29%) and judgement only (26%). Against the specific data types we find statistics are most heavily used with orders and shipments data; this fits well with with common univariate time series forecasting methods. Causal data of various types are integrated through more judgemental means; this is consistent with the lack of advanced forecasting method usage.

Level of Aggregation

Forecasting is generally in monthly time buckets and at the item level. Firms sometimes also forecast in weekly periods, with those engaging in CPFR and other forms of collaboration more likely to forecast weekly. With regards the product hierarchy levels, forecasting at the customer/item level is also relatively common. Companies engaging in collaboration (especially CPFR) are more likely to forecast further down the hierarchy at the item/customer DC or item/store level.

Software in Forecasting

Spreadsheets are far and away the most common and highly used type of software, however they are not the most satisfactory. Specialist forecasting systems are the most favourably ranked of all of the software types. ERP systems were the second most commonly-used and rank just above spreadsheets in terms of user satisfaction.

Account-specific differences

Firms classified in the CPFR grouping are considerably more likely to customise their forecasting approach based on the customer for whom they are forecasting. They show greater levels of flexibility in forecasting approach, statistical methods, frequency, horizon and supply chain level with greater variation per customer than their less collaborative peers.

Accuracy Benchmarks

With regard to error measures, the average 1 month and 3 month ahead item level MAPE is reported to be around 40%. Further work is required to validate this data before it can be reliably used to measure forecasting performance as a number of respondents appear to have given very high error figures. We believe that some of these responses refer to firms' accuracy rather than error statistics. It is, therefore, a concern that firms may not be accurately measuring their accuracy and error.

Conclusions

Reliance on Judgement & basic stats

We have seen that a range of useful data is available and collaboration is common. Respondents indicate that both collaboration and the data it yields are important to accuracy. However, forecasters tend to rely heavily on judgement, despite the inherent bias and inefficiencies associated with it. We find that sub-optimal forecasting techniques are used, compromising the forecast accuracy which can be obtained.

Seeking reasons and remedies for this sub-optimal approach, firms report that data is commonly shared in an unstructured format with limited consistency across CIS partnerships. Once available in the right format, the next challenge is to be able to use key information with the right statistical models to produce a an accurate baseline. Clearly this requires automated data transfer and integration in combination with forecasting software able to use it appropriately.

Additional conclusions and the next steps in our research are outlined on pages 34-37.

2 Introduction

In this report we will present the results of Lancaster Centre for Forecasting's study into Supply Chain Forecasting: Best Practices & Benchmarking. We will show a series of analyses relating to various areas of forecasting under collaborative supply chain partnerships.

Forecasting is of critical importance to firms as they try to compete in a tough marketplace. The purpose of this research is to investigate how manufacturers are forecasting, both in their collaborative and information-sharing (CIS) partnerships with retailers and distributors (customers) in conjunction with internal collaboration between departments.

We seek to identify differences in practice between alternative CIS schemes in the process. The CIS schemes investigated include Sales & Operations Planning (S&OP), Vendor-Managed Inventory (VMI) and Collaborative Planning Forecasting & Replenishment (CPFR). Partnerships with other (non-VMI and non-CPFR) customers may exist, providing downstream data which can be used in planning (INFO). A description of these collaborative practices follows on the next page.

There is a considerable body of existing research, much of it published in the practitioner literature or through industry group studies, which documents case studies and provides anecdotal evidence of collaboration & collaborative forecasting. These prior studies have focused on the collaborative set-up (typically CPFR) far more than the implications for forecasters. This literature tends to discuss inter-organisational processes, the setting-up of business agreements, benefits and barriers, organisational factors and collaborative software solutions.

This research will provide sufficient detail to document key aspects of forecasting under collaboration which are missing in the literature. We used an online survey between January and August 2012 to collect data from 265 forecasting professionals. 200 of these were classified as being in the manufacturing sector and they form the basis of the remaining analysis. Further details about the sample breakdown and survey methodology can be found in the Appendix.

We further classified the responses into 5 groups based on their involvement in various collaboration schemes. To be classified, a response was required to show clear evidence of fitting the group in which it was placed. As a results only 173 of the 200 manufacturers were classified. The full classification logic is documented in the Appendix.

The groups were as follows: CPFR (62 respondents), VMI (18), S&OP + INFO (27), S&OP (59) and SILOS (7). The SILOS group contains firms who participate in almost no internal or external collaboration. 27 of the respondents did not clearly fit a classification and are excluded from the analysis.

The report will continue with a detailed analysis of key results, broken down by the classification groups described above.

3 Detailed Analysis of Results

3.1 Involvement in Collaboration and Information-Sharing

This section focuses initially on whether firms in the sample are currently involved in different supply chain collaboration schemes. These collaboration schemes may operate either inside the organisation, as is the case with S&OP, or with external trading partners such as retailers and distributors. External collaboration types include VMI, CPFR and other data-sharing partnerships.

After showing, on a yes/no scale, the forms of collaboration firms are involved in, we will show how much of each collaboration scheme they practice. The section will continue with analysis of which data from inside and outside the organisation is available to forecasters. We will further report on the time horizon, exchange method and consistency of information shared by collaborative partners.

3.1.1 Collaborative Involvement

We asked respondents which forms of collaboration they are currently practicing. The types of collaboration are defined before the question:

- Sales & Operations Planning (S&OP) - an internal business process which seeks to balance supply and demand in line with strategic and financial objectives. Underpinned by a consensus demand forecast between departments.
- Vendor-managed Inventory (VMI) - a business process where the supplier takes responsibility for managing inventory levels at customer stocking locations. Order quantities are determined by the supplier using data (e.g. shipments from and stock levels at the distribution centre) provided by the customer via Electronic Data Interchange (EDI).
- Collaborative Planning, Forecasting & Replenishment (CPFR) - this advanced form of collaboration is an inter-organisational business process where partners reach a consensus forecast through high levels of collaboration & data-sharing, joint forecasting and exception management. CPFR will typically also include joint planning (e.g. promotions), regular performance review and allocating responsibility for inventory. CPFR partnerships can work at varying levels of the supply chain and may only cover certain categories or items, such as new or promoted items.
- Other information-sharing partnerships (INFO) - other less-formalised customer partnerships which are neither VMI nor CPFR but still involve data exchange for possible use in forecasting.

Companies who do not participate in any of the other types of internal and external collaboration are shown in the SILOS category in figure 1.

Q1: Is your organisation involved in these types of collaboration?

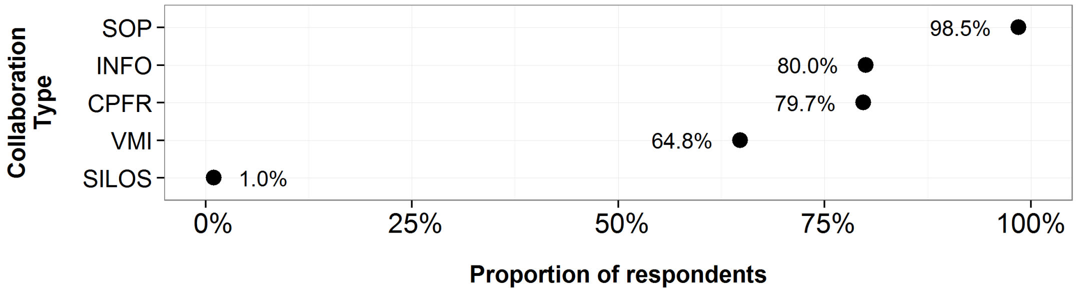

Figure 1: What forms of collaboration are you involved in?

Interpreting figure 1 shows that within our sample only 1% of respondents could be truly classified as forecasting in silos. These two companies are involved in no collaboration whatsoever and scored zero for each of S&OP, CPFR, VMI and INFO. This is in stark contrast to the proportion of companies who are involved in S&OP to some extent. 98.5% of respondents are involved in S&OP and this is by far the most likely form of collaboration to be practised.

CPFR is the next most likely with 80% of respondents involved. Other information-sharing is equally as likely at 80%. VMI is the least likely to be practised however 65% of respondents are involved to some extent.

Key take-away point: 99% of companies practise S&OP to some extent and 85% participate in at least one type of external collaboration or information-sharing.

Extending the analysis from whether companies are involved at all in collaborative schemes, we will report the level of involvement across the sample. The distribution of responses from 'Never' to 'Always' shows clear differences in the level of participation between the different schemes. Figure 2 contains the results of the next question.

Q2: To what extent is your organisation involved in these types of collaboration? (CPFR, VMI, S&OP, other sharing)

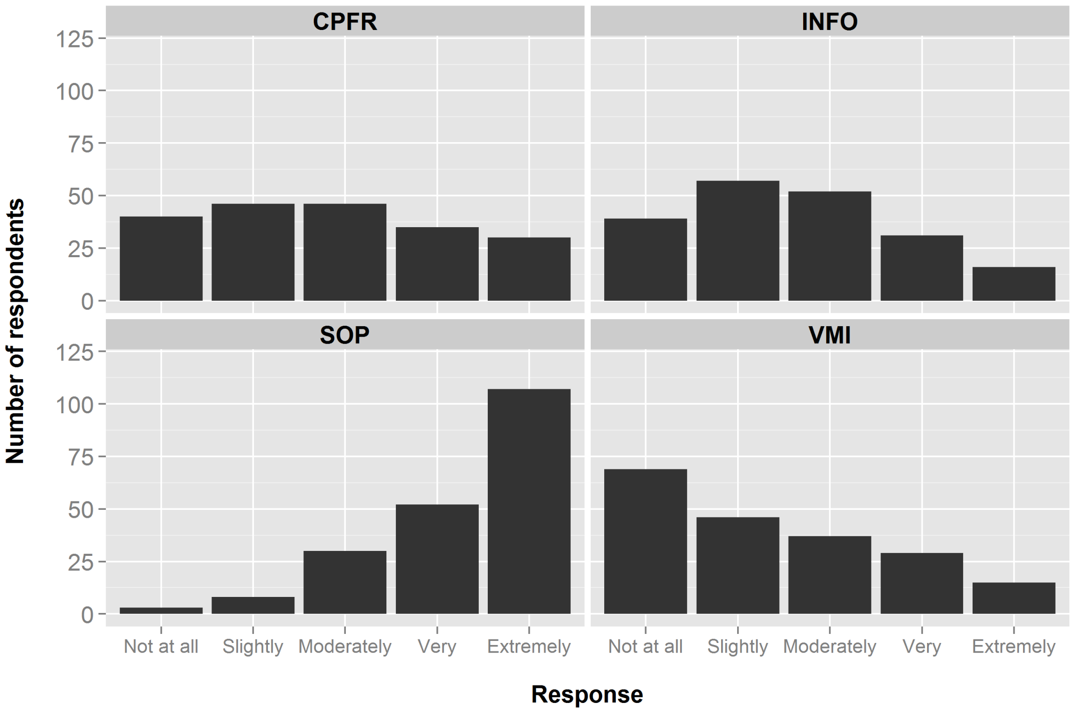

Figure 2: How much do you participate in different forms of collaboration?

The first point to make about the relative distributions in figure 2 is that S&OP is the most commonly practised as well as the most widely practised form of collaboration. The distribution of responses is highly skewed to the right, 54% are 'Extremely Involved' in S&OP with only a handful of respondents 'Slightly Involved'. This is contrasted with VMI which shows the reverse pattern. Companies are more likely to be 'Not at all' involved in VMI than 'Extremely Involved' in it.

At first glance the distribution of responses for CPFR and INFO are similar but closer inspection shows that firms report more involvement in CPFR than other data-sharing.

Further analysis of the responses shows that firms are involved in multiple forms of collaboration simultaneously. 92% of firms participate in some level of S&OP plus a degree of external CIS. 34% of firms who participate in external CIS will be involved in two distinct forms and 52% will be involved in all three. 59% of the 200 respondents participate in some degree of S&OP, VMI and CPFR in parallel.

Key take-away point: S&OP is widely practised and firms are extremely involved with it. They are more heavily involved in CPFR than INFO and VMI is the least widely practised. Firms are also typically involved in the different forms of CIS together.

3.1.2 Information available to forecasters

In order to measure the amount of information-sharing taking place with trading partners and to assess the level of data available to the forecaster from within the organisation, the following question was posed:

Q3: To what extent are the following types of data available?

The data types included in external and internal data groupings are provided below:

<u>Internal data:</u>

- orders & shipments at the item, customer and customer/location level
- stockouts and unsatisfied demand
- promotions/trade marketing activity
- assortment changes & new product introductions
- media marketing activity
- Nielsen/IRI scanner data

<u>External data:</u>

- sales & order forecasts at the item/customer and item/location level
- stockouts or shelf availability/lost sales estimate
- promotional plan at account and ship-to level
- product listings/de-listings
- EPOS data
- shipments from customer distribution centres (DC withdrawals)
- stock levels at customer DC and store
- regular price changes.

Each item was measured on a five-point scale from 0 (Never) to 4 (Always). The overall score for internal data and external data consists of an average per respondent across 11 (internal) and 13 (external) distinct data types.

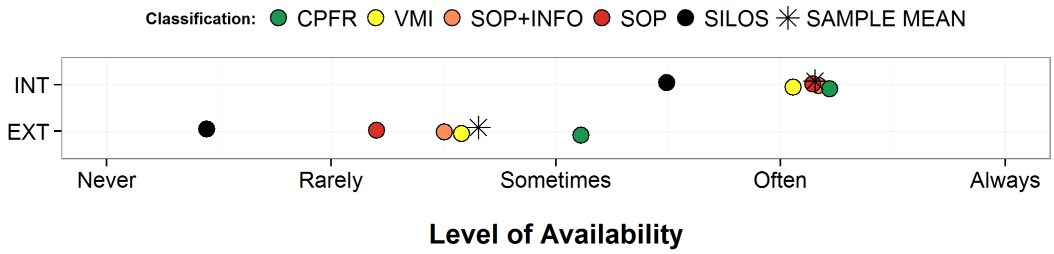

Figure 3: Data available to forecasters. Shows the average availability level for internal versus external data

There are four key points regarding the availability of internal and external data as shown in Figure 3. Firstly, internal data is far more available than external data. The sample mean for internal is around 'Often' whilst for external data it lies midway between 'Rarely' and 'Sometimes'. Secondly, the data points are much more tightly grouped for internal data than for external data. This shows that the classification has more effect on external data availability than internal data availability. Thirdly, the ordering of the points shows that silos are consistently behind the others. This is to be expected as companies in the SILOS classification are the least collaborative, engaging rarely in S&OP or external collaborations. Finally, and in contrast to the SILOS group, the CPFR group are the only group to be above the sample mean for external data.

Moving on from aggregated internal and external availability measures, the next question covers the 11 specific internal data types. Internal data is defined as data which is passed to forecasters from within the organisation. Some of this data may originate from outside the firm (e.g. promotions and assortment changes), however it is classed as internalised before it reaches the forecaster.

Q4: Which information is available internally for forecasters? (i.e. provided from within your organisation and not directly from the customer)

Figure 4 shows the internal data availability for 11 distinct data types.

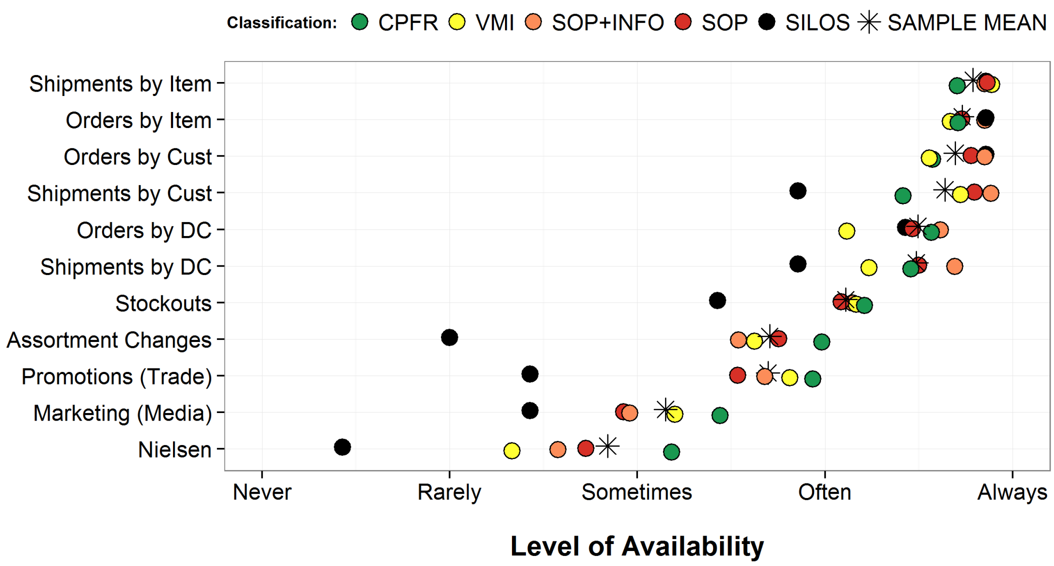

Figure 4: Internal Data available to forecasters. Shows the average level of availability for each type of data

Information availability within the organisation in general is high, as shown in Figure 4, however it varies considerably for different data types. Comparison of the sample mean scores across all 200 responses shows that transactional data (orders & shipments) has the highest availability whereas causal information (e.g. promotions, listings/delistings and marketing plans) is, on average, less readily available. The chart is dominated by orders and shipments at the various levels. A pattern can be seen within the transactional data types whereby availability decreases as the data becomes more detailed or granular (i.e. at the customer or customer DC level).

Within our classification scheme there is a clear pattern which emerges. For transactional data at the item level, the dots are closely grouped, however items displayed lower in the chart have a greater spread between the points. Causal data types are consistently more available in the CPFR group than the sample mean. Furthermore, the SILOS group lags way behind.

Now looking at external data availability, it is documented that data supplied by downstream trading partners may be available for manufacturers to integrate into their planning process. Studies have shown that this is able to improve forecast accuracy and drive improved supply chain performance. We know of no prior large-scale studies which have reported on these different measures of external data availability.

We presented a list of 13 external data types and asked each respondent to rate how available each type of information was to them. As before, each question was answered on a five point scale ranging from 'Never' to 'Always'.

Q5: Which data is provided directly to you by customers who share information?

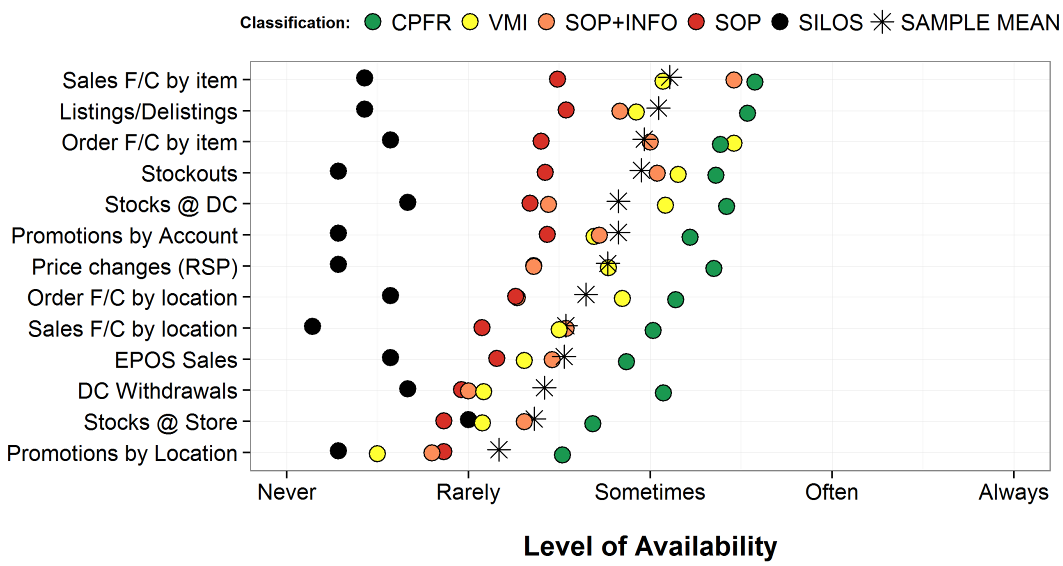

Figure 5: External Data available to forecasters. Shows the average level of availability for each type of data

Figure 5 shows that the sample mean level of availability for external data types is only twice above the midpoint ('Sometimes' available). There is a greater likelihood of this data being unavailable than was the case with internal data. In the ranking of data types, sales forecast by item, listings/delistings and order forecast by item are the most available type of external data. Other data types are less available with promotions by account, EPOS sales and DC withdrawals (sell-through data) at the bottom of the rankings, along with the more granular data such as forecasts by location and store stock levels.

Comparison of the groups show that the CPFR (green) group is consistently out in front by a significant margin. The S&OP (red) and SILOS (black) groups are consistently below the sample mean. The VMI (yellow) and SOP+INFO (orange) groups vary around the mean and typically fill the gap between CPFR and S&OP or SILOS. Overall, the spread between the points is high for external data, showing the importance of formal collaboration to data availability from trading partners.

Key take-away point: Internal transactional information is the most readily available data and other types of information such as promotions and marketing plans are less frequently available. More granular transactional data is also a little less available. External data is much less available in general and firms most involved in formal collaboration have more data at their disposal. Sales & order forecasts at the item level and listings/delistings are the most commonly shared types of data.

It is also of importance to forecasters that the data is available early enough to be of value. The next section will investigate the horizon of external data-sharing for the following data types: sales forecast, order forecast, promotional plans, assortment changes. The question was only displayed when a respondent had earlier answered that the specific data type was available to some extent.

Q6: How far into the future do customers usually provide this information?

The options were as follows:

- less than 2 weeks
- 2-4 weeks
- 5-8 weeks
- 9-13 weeks
- more than 13 weeks

Figure 6 shows results from the horizon of shared data question, displaying the alternative classifications against the sample mean for the four types of external data shared.

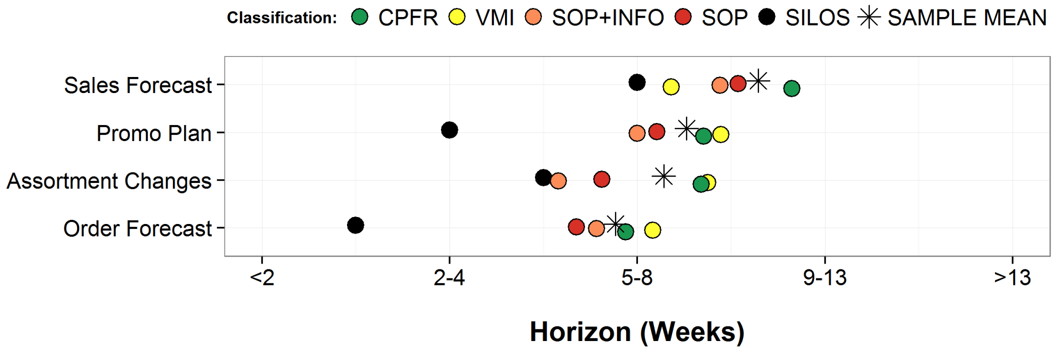

Figure 6: Horizon of shared data. Shows how far in advance trading partners share each type of data

In figure 6 we see that the sales forecast is shared with the longest lead time, followed by promotional information and assortment changes (including listings/delistings). Customer order forecasts have the shortest horizon at around 5-8 weeks, perhaps indicating the level of difficulty in creating a time-phased order schedule which takes into account inventory and distribution-related parameters.

Of the five groupings, the CPFR and VMI groups have the longest horizon of external information. This is to be expected with CPFR and its formal agreements, however for VMI to rank so highly is interesting. It may indicate that VMI partnerships are far richer in information-sharing and have overcome some of the limitations reported in early implementations where a lack of visibility of causal factors impacted forecast accuracy and led to stock availability issues. In our sample, the other groups (S&OP and S&OP+INFO) are consistently below the sample mean and SILOS is invariably further behind in last place.

The format in which data is exchanged by trading partners is of importance to forecasters. It will directly impact on their ability to easily and systematically integrate it into their forecasting. Prior studies have described a range of information exchange methods which vary in their level of sophistication, structure and scalability. In order to find out about this in practice we identified six methods of information exchange to include in the survey. These are shown below:

- Email (including attachments)
- Telephone
- Face-to-face
- Structured messaging or Electronic Data Interchange (EDI)
- Direct system access to downstream data (e.g. WalMart's RetailLink portal)
- Collaborative platform

The question was posed for each of the data exchange methods as follows:

Q7: By which means do your customers share this data (Never-Always)?

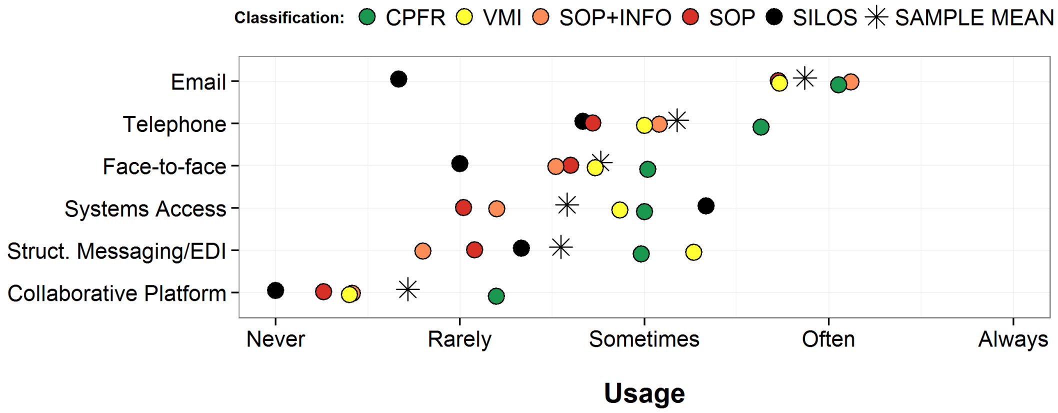

Figure 7: Exchange methods for shared data. Compares how downstream trading partners share data

As shown in figure 7, there is a clear tendency towards less-structured methods, with email, telephone and face-to-face the three most likely methods of data exchange. Email was significantly out in front. The more structured methods of systems access, structured messaging/EDI and collaborative platforms are ranked at the bottom of the list. In fact, collaborative platforms were scored significantly lower than the other methods of data exchange within the sample.

There is again a pattern between the groups with CPFR out in front in all but one area (structured messaging/EDI). It is, however, to be expected that VMI companies will rely heavily on EDI messaging as it forms a cornerstone of the VMI model.

We have seen that firms collaborate and share data with trading partners. Multiple forms of collaboration can exist in parallel and firms can collaborate differently with different partners. The next question relates to the variations in data exchange between the respondent and their CIS partners. Respondents we asked to specify whether they agree or disagree with a set of statements regarding consistency in their CIS partnerships. The question and statements are shown below.

Q8: Do you agree or disagree with the following statements?

- Information-sharing is consistent (similar) from customer to customer
- Our customers share the same types of data (e.g. EPOS, forecasts, stocks, promos)
- Our customers share data at the same level of aggregation (account/warehouse/store)
- Our customers share data in the same time buckets (days/weeks/months)
- The method of data exchange is the same for all customers

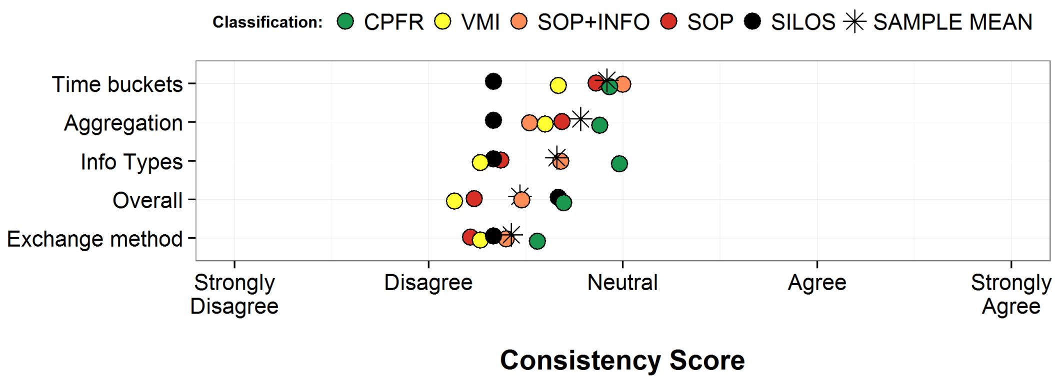

Figure 8: Data consistency between collaborative partnerships.

In figure 8 the sample mean is to the left of centre, indicating that firms find CIS partnerships inconsistent in terms of data-sharing. This was the case for all 5 of the statements in the survey. The time buckets of the data are the most likely to be consistent whilst the exchange methods varies the most.

Key take-away point: Customers share data in a range of ways, the most commonly used methods being relatively unstructured in nature. Email is clearly the most widely used means of communication. Data exchange is not consistent between trading partners and differences exist in a range of areas. Companies classified as heavily involved in CPFR report more structure and consistency in their data-sharing partnerships with customers.

3.2 Forecasting Practice

This section covers the forecasting-related items of the survey. We will begin by following on from the previous section on data availability and show how internal and external data are used in forecasting. This will be followed by respondents' overall forecasting approach and their level of forecasting aggregation.

3.2.1 Use of data in forecasting

Section 3.1.2 showed that different types of data are available in varying degrees to forecasters. Once the data is available, forecasters have a choice of whether to use it or not in forecasting. Factors such as accuracy of the information, the time periods of the information, the sheer scale of data, the skills of the forecasters and the IT capabilities of the organisation will all influence whether the information is used.

A forecaster has a range of techniques available to use with time series data or other specific useful information in forecasting. There is a wide body of research into the use of statistical methods and judgement in forecasting. We have seen that internal data is widely available, the next question is whether it is used in forecasting. The following 2 analyses, on use of internal and external data in forecasting, will now show the results.

Q9: How is internal data used in forecasting?

- Not used in forecasting
- Only Judgement
- Mainly Judgement
- Equal mix of Stats and Judgement
- Mainly Statistics
- Only Statistics

The analysis presented in figure 9 excludes responses where data is either unavailable or unused. Due to the fact that many companies reported unavailability or no usage of certain data types, the number of observations used to calculate the group means is lower.

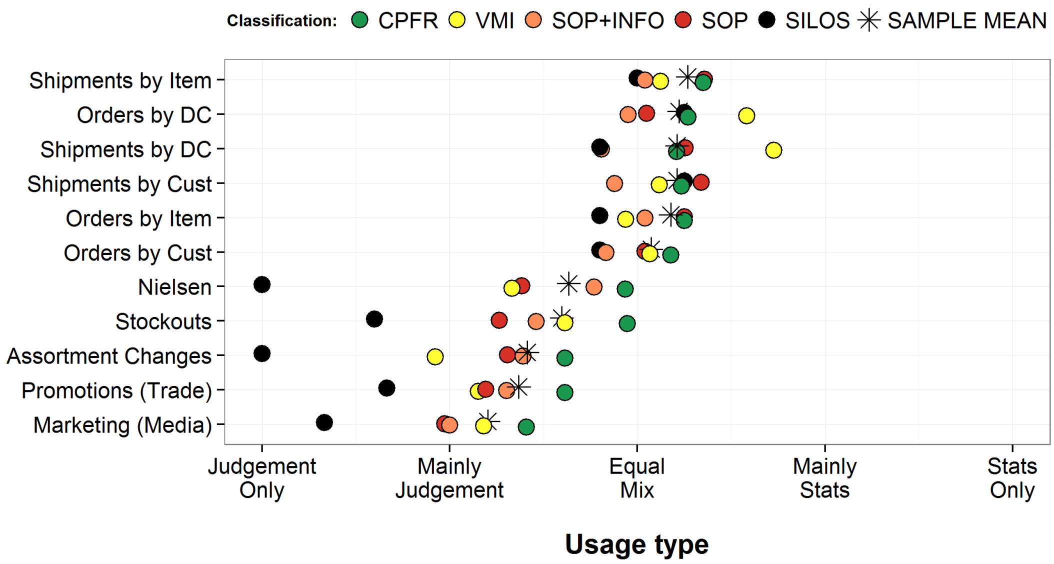

Figure 9: Internal Data use in forecasting

Figure 9 shows a clear split in how data is used by forecasters. There is a clear distinction between the responses for orders and shipments (top 6 items in the chart) and the rest of the data types. For these transactional data series, forecasters are using more statistics than for any of the other data type. There is a marked drop to Nielsen data, and even less reliance on statistics for the remaining types of data. The purely causal data types such as assortment changes, promotions and marketing data are more likely to feature a greater degree of judgement.

Whilst the classification groups are well clustered and at a similar level for shipments and order history, the contrast between the different groupings becomes greater and a clear pattern emerges. The CPFR group is ahead of the other groups on a consistent basis and these companies report that relatively more statistical forecasting is used.

We posed the same question for the external data types which are shared by trading partners down the supply chain.

Q10: How is external data used in forecasting?

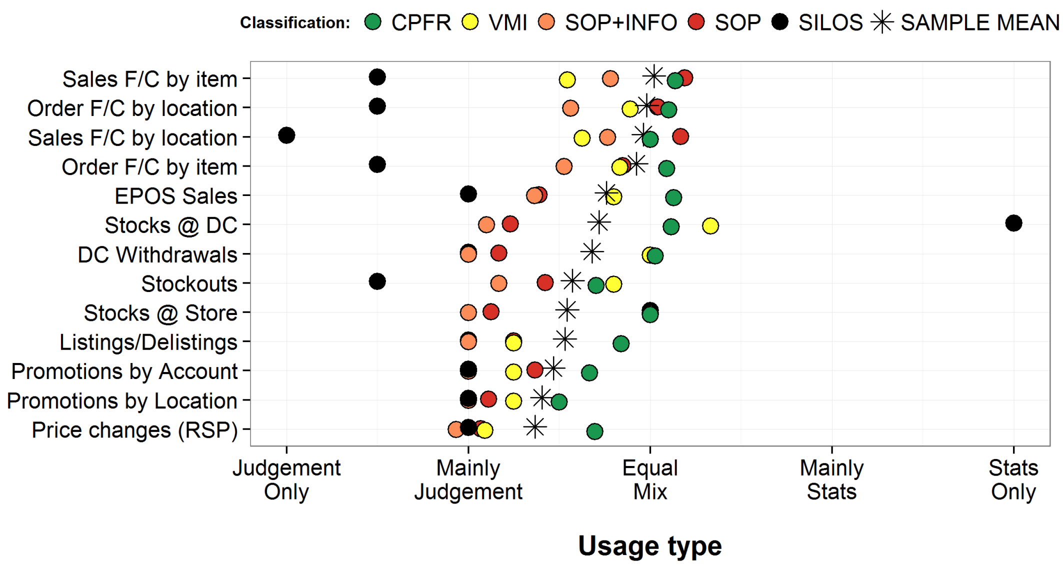

Figure 10: External Data use in forecasting

The chart of external data usage in forecasting (Figure 10) displays the sample mean in the left half for all data types, indicating that judgement outweighs the use of statistics when incorporating external data into forecasts. The highest levels of statistical usage are with sales and order forecasts followed by DC stock levels and POS data. Judgement is used most with causal data types and the four highest data types ranked with most judgement are (regular) price changes, promotions and listings/delistings.

Comparing the patterns between different classifications shows that the points are clearly dispersed and that the CPFR group is significantly ahead of the sample mean whilst the collaboratively less advanced groups lag behind the mean.

3.2.2 Overall forecasting approach

In order to assess their overall forecasting approach and investigate the use of statistics, judgement and a mixture of the two in forecasting we asked respondents to provide a percentage of their final forecasts which are produced using each approach.

Q11: What percentage of your final forecasts consist of the following approaches?

- Statistical methods alone (i.e. without judgemental adjustment)
- Judgemental methods alone (i.e. no statistics)
- A statistical forecast with judgemental adjustments

Each item was scored 0-100% with the total across the three distinct approaches adding up to 100% per respondent.

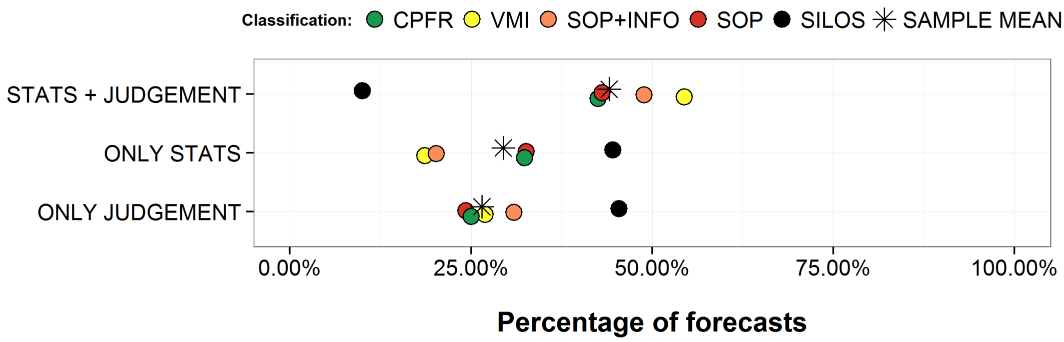

Figure 11: Overall forecasting approach. Shows the how forecasters use statistics, judgement and a combination of the two approaches in forecasting.

The most common approach among forecasters was a statistical baseline with judgemental adjustment, with a sample mean value of 44%. The second most popular approach was a purely statistical forecast with no judgemental adjustment (29%) and finally a purely judgemental forecast (26%). This supports the view that judgement is a key component of supply chain forecasting practice, despite evidence that statistical methods are able to outperform it under certain circumstances.

Key take-away point: Practitioners report that judgement and statistics feature heavily in their forecasting, both separately and in combination. Statistics are used most with orders and shipments data, which fits with common time series forecasting methods. Causal data of various types are integrated through more judgemental means.

3.2.3 Use of statistical methods

A body of research has linked the use of suitable statistical methods to forecast accuracy. Other studies have sought to provide empirical evidence of the use of different forecasting algorithms in practice. Our research is new and it fills the gap caused by a lack of recent survey research in forecasting practice. We will explore the problem from a new perspective: collaboration, and provide a higher level of analysis by grouping forecasting methods into a classification of TIME SERIES and ADVANCED TIME SERIES &

CAUSAL.

Q12: What percentage of statistical forecasts are made with these methods?

The statistical forecasting techniques we identified are listed below. Respondents answered between 0-100% for each method, with answers adding up to 100% per respondent.

(T) TIME SERIES:

- Exponential Smoothing family of models
- Random Walk/Naive (same as last period or same as last year)
- Average or Moving Average
- Models for lumpy/intermittent demand (slow-moving items)
- Decomposition

(A) ADVANCED TIME SERIES + CAUSAL:

- Regression with explanatory variables
- ARIMA
- Lewandoski
- Neural Networks

Figure 12 shows the breakdown for the individual forecasting methods. Note that ADVANCED methods are tagged with an asterisk ('*').

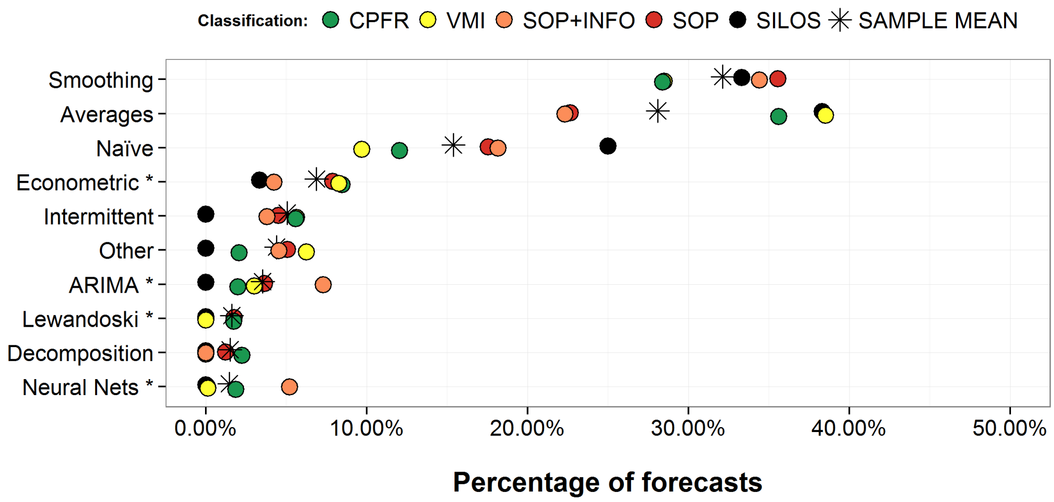

Figure 12: Use of statistical forecasting methods. Shows the how forecasters use statistics to generate forecasts.

Comparing the sample mean for each of the different forecasting methods in Figure 12 shows that the smoothing family of models are highest ranked (32.1%) with averages second at 28.1%. They were followed by the naive (15.4%) and a host of other forecasting techniques below the 10% mark. The forecasting methods which prevail are the simpler univariate time series methods with the top 3 ranked methods listed above accounting for 75.6% of all forecasts.

Advanced time series and causal methods are subsequently far less used by forecasters. These types of models, which are ideally suited to the causal and other time series data available through collaboration, are seldom used. Econometric (6.9%), ARIMA (3.5%), Lewandowski (1.6%) and neural nets (1.5%) account for only 13.5% of statistical forecasting.

At this level of detail, with 9 different forecasting methods considered, it is difficult to see a clear pattern between the collaboration types. However, the high values for the CPFR and VMI groups for averages are surprising. We expected that they would rely more heavily on the smoothing family of models which offer greater flexibility and out-perform averages in many situations. This raises the question as to why and how they are using averages, possibly that they are using them to average their own forecast against the forecast supplied by the retailer. We will report on this after follow-ups with specific practitioners. In further analysis we will report at a higher level of aggregation, contrasting TIME SERIES techniques against ADVANCED techniques in order to see differences between the classifications.

Follow-up analysis is also planned to investigate the number of different forecasting techniques employed. For example, a number of respondents use only a single forecasting method, such as smoothing (19 respondents), averages (6), Naive (5), other stats(4), Lewandowski (3), econometric (2) and neural nets (1). It will be interesting to see whether collaborative leading firms are more likely to have greater diversity in model selection.

Key take-away point: The simpler univariate class of methods are most widely used in forecasting, led by smoothing, averages and the naive method. They account for 82.1% of all statistical forecasts. Advanced methods, capable of leveraging promotional and downstream data, are much less widely used (13.5%).

3.2.4 Level of forecasting aggregation

Aggregation in forecasting is an important topic because it has implications on the number of series which have to be forecast, the demand variability and the likelihood of zeros in the time series. This in turn effects the forecastability of the series and resulting accuracy. Computing power is a factor here as it has been reported that some major retailers have in excess of 1,000,000 forecast items at the SKU/store level.

Prior studies have shown that manufacturers forecast in monthly buckets, including 4-4-5 and 13 x 4 variants, at the item level. Studies in the CPFR literature describe collaborations where forecast data is exchanged at the weekly level and hence weekly forecasting is required from both parties. Under reported CPFR agreements, partners may focus their collaboration on the customer Distribution Centre or even the store level.

Aggregation can be split into to two elements:

- Periodicity - the time buckets being forecast (days, weeks, months)
- Channel aggregation - item level, customer level, customer DC level, POS level

To discover the level of aggregation in manufacturer forecasting in these two areas, we asked the following questions:

Q13: What time buckets do you forecast in?

For each of the levels of time aggregation the following responses were available:

- Never
- Rarely
- Sometimes
- Often
- Always

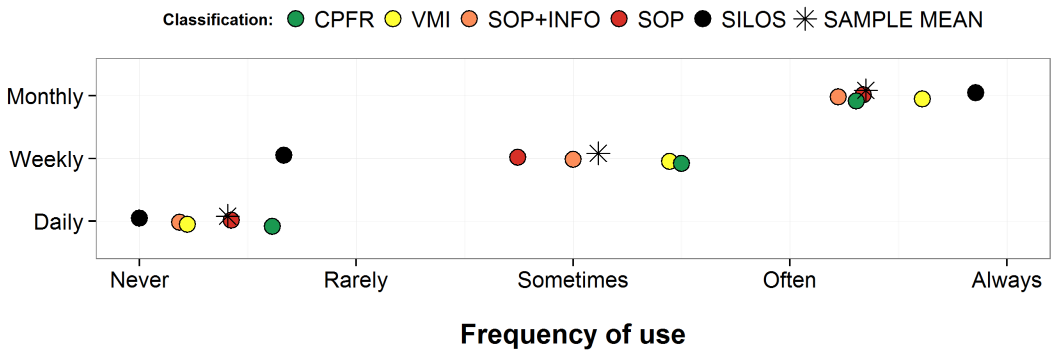

Figure 13: Time buckets used to forecast. Shows the daily, weekly and monthly forecasting comparison.

Forecasts are most often generated in monthly buckets as shown in figure 13. Weekly forecasting is significantly less likely across the whole sample and daily forecasting is even less likely to be practised.

The CPFR group are considerably more likely to forecast in smaller time buckets, in particular with a higher frequency for weekly forecasting. The SILOS and S&OP groups are less likely to forecast weekly or daily, indicating that collaborative involvement leads to more granular time periods in forecasting.

Key take-away point: Monthly buckets are most often used, however firms sometimes also forecast in weekly periods. Companies engaging in CPFR are more likely to forecast weekly

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The second element of granularity or aggregation is the level of the supply chain at which companies are forecasting. To measure this we asked respondents the following question for each of the levels at which they may forecast:

Q14: For what percentage of customers do you make the following forecasts?

- item level (multiple customers aggregated)
- customer or account level
- customer DC level
- POS level

Figure 14 shows the results of the second granularity question regarding the level of the supply chain at which companies forecast.

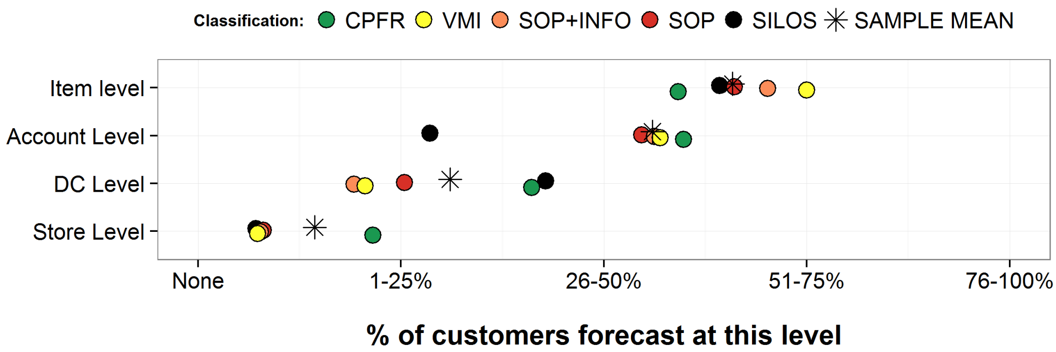

Figure 14: Supply Chain level used to forecast.

Inspection of Figure 14 shows a similar pattern to the answers to Q13 about time buckets and less granular forecasting is the norm. The ranking of items by sample mean shows firms are most likely to forecast at the highest level of aggregation (item level). Forecasting in more detail is progressively less likely. As aggregation decreases to the DC and store-level we find a significantly lower score is reported.

Similar again to the previous question about time buckets, the CPFR group are considerably more likely to forecast at lower levels of aggregation. In particular, the CPFR group are significantly more likely to forecast at the DC or store level. Interestingly, the groups are closely clustered for customer-level forecasting, indicating that most companies also forecast at the customer level regardless of their collaborative classification. The SILOS group is the exception to this, with these companies rarely forecasting at the customer level.

Key take-away point: Item level forecasting most often used, however firms also forecast at lower levels of aggregation. Companies engaging in CPFR are more likely to forecast further down the supply chain hierarchy.

3.2.5 Flexibility in forecasting

This section will address the question of whether companies vary elements of their forecasting practice or configuration to cater for the differing needs of their customers. During the course of the survey we asked respondents to provide details about customer-specific forecasting variations.

Q15: In what ways does forecasting practice differ from customer to customer? (i.e. account-specific differences in forecasting)

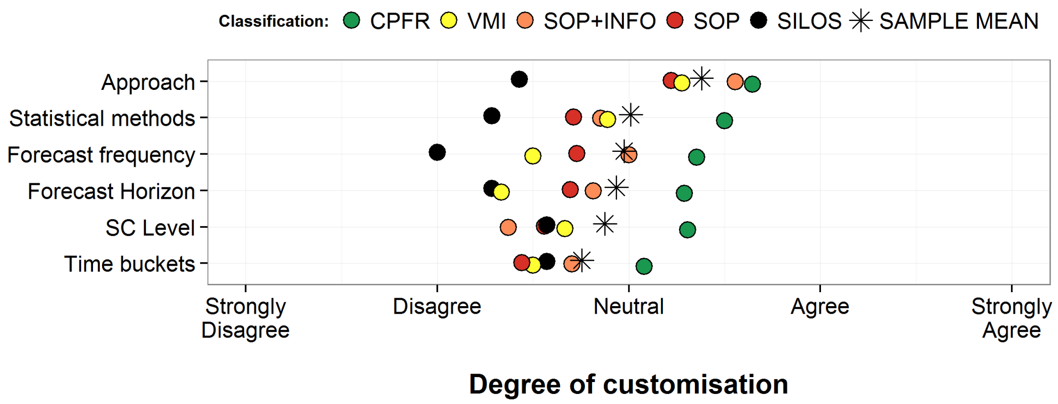

Figure 15: Forecasting variations for different customers. Shows the extent to which forecasting differs.

There are two key observations in figure 15. Firstly, the forecasting approach is the most likely aspect of forecasting to be varied for different customers. This is the only response where the sample mean is above the midpoint. Secondly, and perhaps more importantly, the CPFR group are significantly more likely to vary their forecasting for different customers. The CPFR group are well ahead of the sample mean for all of the aspects investigated.

Key take-away point: Companies in the CPFR grouping are considerably more likely to customise their forecasting approach based on the customer for whom they are forecasting

3.2.6 Software in forecasting

The importance of software in the forecasting process has been documented in prior research. In order to generate the best forecast for large numbers of items, firms have implemented forecasting software to facilitate the task. Forecasting software can be classified into a number of categories. Prior literature and case studies tell us that firms use some, all or none of the following types of software in forecasting:

- Spreadsheets (with or without customisation)
- ERP/MRP system modules designed for forecasting
- Specialist forecasting software
- Custom-built solutions
- A collaborative forecasting platform between trading partners
- Demand sensing software

In this section we will investigate the different types of software used to support the forecasting task. Initially, respondents were asked whether they used a particular type of software. The question was worded as follows:

Q16: Do you use these types of software in forecasting?

We have first coded responses with a binary (yes/no) variable to show whether a specific type of software is used. Responses stating 'Never' scored 0 and all other responses scored 1. Taking an average of responses for each variable gives the percentage of respondents who, to some extent, use a particular type of software. Results of Q16 are shown in figure 16.

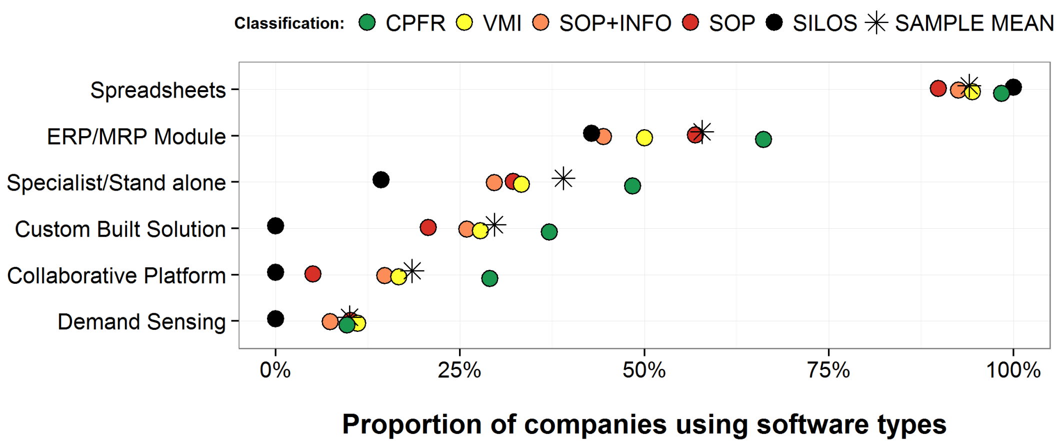

Figure 16: Types of software used in forecasting (yes/no)

In keeping with prior studies, figure 16 shows that spreadsheets are the most commonly used type of software in forecasting. More than 95% of respondents use spreadsheets to some extent. The next most common software type is an ERP/MRP forecasting module (57%). 38% of companies used specialist software and 27% of respondents used a custom built solution to support forecasting. The least common types of software are a collaborative platform (18%) and finally demand sensing which only 10% of respondents used in forecasting.

Moving on from the binary yes/no response, we sought to clarify how often forecasters use each type of software.

Q17: How often do you use these types of software in forecasting (Never - Always)?

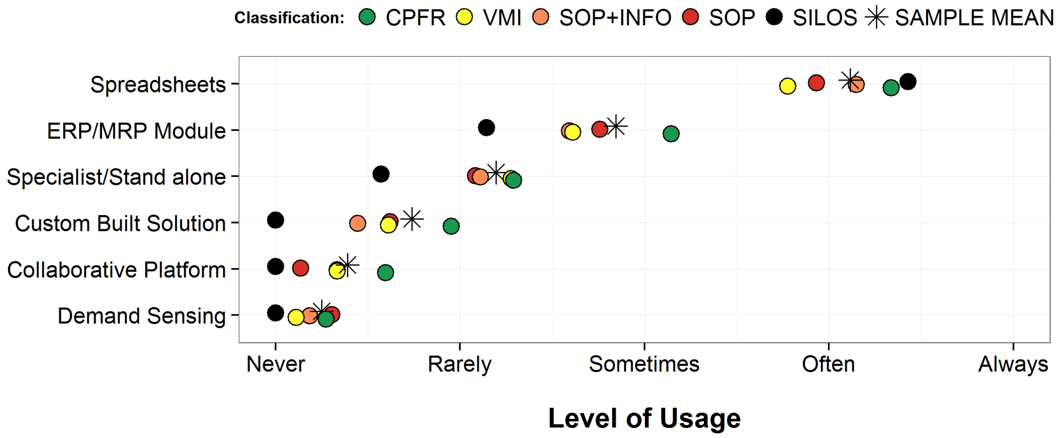

Figure 17: Level of software usage

In line with the responses to Q16 (about the types of software used in forecasting), figure 17 shows that spreadsheets are also the most heavily used type of software in forecasting. The sample mean indicates that spreadsheets are at least 'Often' used by forecasters. ERP/MRP forecasting modules were a clear second, the sample mean being just below 'Sometimes'. Use of a specialist or stand-alone package is once again in third place.

With regard to how frequently different collaborative groups use software, it is clear that the CPFR group makes use of software to a greater extent. CPFR out-scores the sample mean for all types of software. In contrast, the SILOS group uses software less than average for all types except spreadsheets.

The next question asked forecasters about their satisfaction with the different types of software used to support their task. Each software type was ranked on the satisfaction scale shown below the question.

Q18: How satisfied are you with your forecasting software?

- Not at all satisfied
- Slightly satisfied
- Moderately satisfied

- Highly satisfied
- Completely satisfied

Respondents were only asked to provide a satisfaction rating for software types that they currently use. The results from Q18 show how satisfied forecasters are with the software that they use.

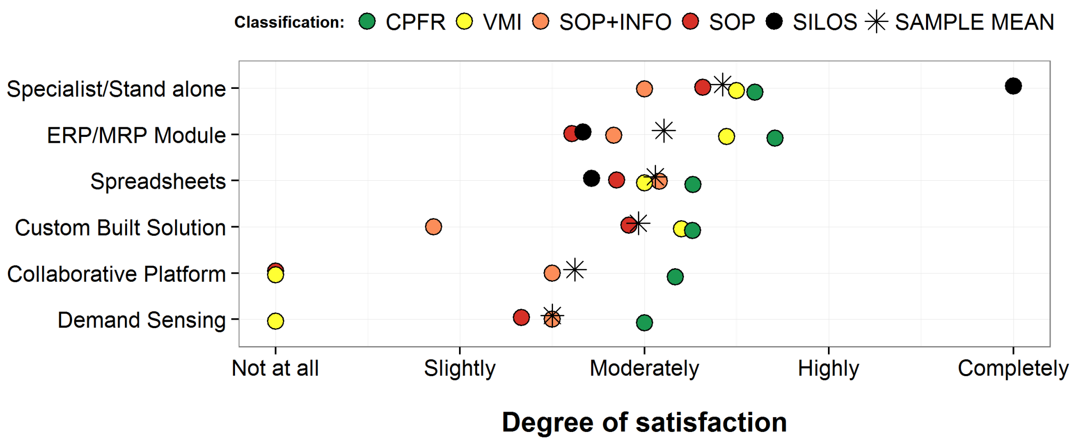

Figure 18: Satisfaction with software.

The satisfaction rating of software types are shown in figure 18. The most satisfactory types of software were reported to be specialist/stand-alone packages. ERP/MRP forecasting modules followed in second place with the most frequently used spreadsheet option ranking third. The remaining three types were not only the least used but also the least satisfactory software types.

In general we see that the CPFR group are the most satisfied with all types of software.

Key take-away point: Excel is far and away the most common and highly used type of software, however it is not the most satisfactory. Specialist forecasting systems are the most favourably ranked of all of the software types. ERP were the second most commonly-used, however they rank just above spreadsheets in terms of user satisfaction. Firms also develop custom and collaborative solutions to facilitate forecasting but to a lesser extent.

3.3 Forecast Accuracy Benchmarks

The importance of forecast accuracy in the supply chain is widely documented. World-class forecasting can be a source of competitive advantage for organisations. In many areas of business firms have sought to compare themselves against their competitors through benchmarking.

The problem with forecasting benchmarks is direct comparability. There are a whole range of reasons why accuracy is not directly comparable from company to company or even business unit to business unit. This is due to differences in the lead time, the forecast time buckets, the level of the product hierarchy, industry sector, sales channels. For a fuller discussion of the issue of forecasting benchmarks, see article by Stephan Kolossa in Foresight (2008).

We asked respondents to give their forecast error, measured as mean absolute percentage error (MAPE), at a horizon of 1, 2, 3 and 12 months ahead for category, item and item/customer levels. Response to each question was optional and limited to 0-100%.

Q19: What is your forecast error, measured as MAPE?

The response rate for the individual questions varied between 24% and 52%. 59 of 200 respondents did not provide an answer to any of the accuracy questions. The table below shows the number of respondents, the sample mean and standard deviation for each of the error measures.

Table 1: Summary statistics - reported MAPE (%) at various forecast horizons and aggregation levels

Level	Horizon	Responses	Blanks	Min	Max	Median	Mean	Stdev
Category	1m	95	105	0	98	25	33.10	27.61
Category	2m	74	126	0	95	25	32.81	23.91
Category	3m	74	126	0	95	30	35.57	23.82
Category	12m	58	142	0	100	35	38.57	25.55
Item	1m	103	97	0	100	31	40.21	24.75
Item	2m	78	122	8	90	35	38.56	19.87
Item	3m	77	123	3	100	39	40.74	20.43
Item	12m	58	142	0	100	50	44.81	23.08
Cust	1m	80	120	0	100	36	39.11	25.37
Cust	2m	68	132	0	100	40	39.11	23.44
Cust	3m	64	136	0	100	40	41.92	25.82
Cust	12m	48	152	0	100	44	43.35	32.01

Further to these summary statistics we will show the error distributions for each of the 12 categories in figure 19. Before showing these figures it is pertinent to warn readers of various potential sources of unreliability. First and foremost, a number of respondents appear to have reported their forecast accuracy rather than their forecast error! This would explain some of the extremely high responses (errors over 80% are unexpected). This anomaly is further evidenced through the fact that some firms have reported a higher error level for their short term forecasts compared to their longer term forecasts. More granular forecasts (e.g. customer location) are not expected to be lower in error than aggregated category level forecasts.

Additional unreliability may be introduced by forecasters not correctly measuring their error and providing a guesstimate. There is also the possibility that somebody may report inflated error statistics in order to lift the sample mean.

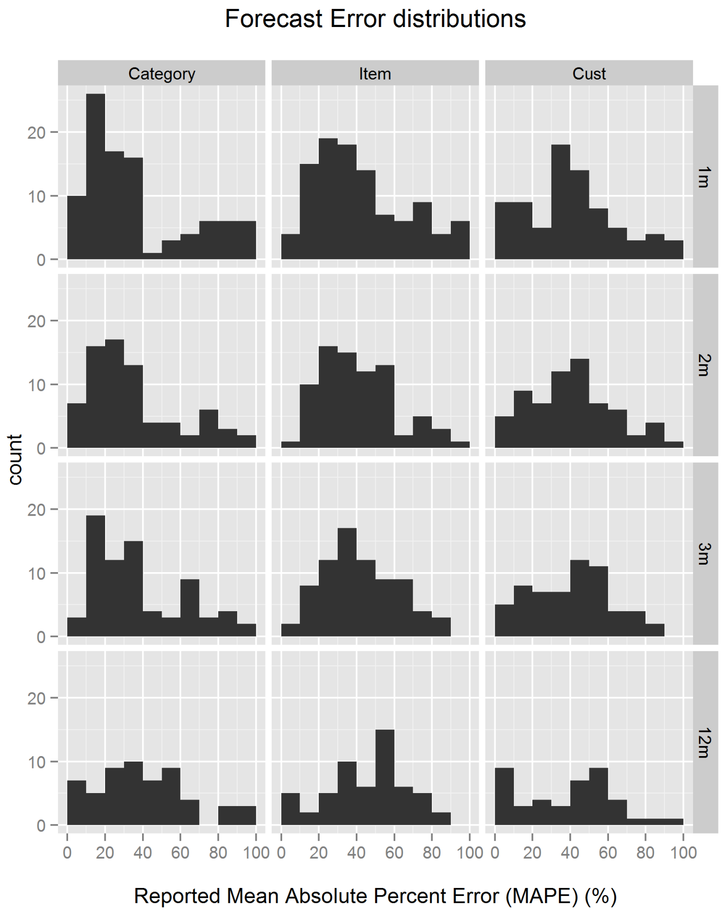

Figure 19: Forecast Error distributions. MAPE (%) given at 1-12m horizons and various levels of aggregation

We see that the errors are mainly clustered in the range 20% to 60%. There are a number of observations which lie outside this range and as can be seen in table 1, the range of most accuracy statistics was 0-100%.

Table 2: Reported MAPE (%) summary

	Aggregation	1m	2m	3m	12m
1	Category	33.10	32.81	35.57	38.57
2	Item	40.21	38.56	40.74	44.81
3	Customer	39.11	39.11	41.92	43.35

The range of average MAPEs across dimensions is 33.1% to 44.8% (see Table 2). A clear trend exists with error increasing as forecast horizon gets longer and error also increasing as the aggregation of forecasts decreases. We can see that the 1m category forecast error is 33.1% against a SKU by customer error of 39.1%. This pattern is to be expected and we expect to see the pattern become more clear following some additional data cleansing we will carry out.

Key take-away point: For the 1 month and 3 month ahead item level forecast error, the sample mean is reported to be around 40%. These figures need to be validated with respondents before their reliability can be assessed.

3.4 Additional Analyses

The final section of analysis in the report will cover four areas. Firstly, we will investigate the importance of collaboration to forecast accuracy. Secondly, the importance of various types of internal and external data are examined in detail and subsequently compared at an aggregate level.

The section concludes by understanding firms' satisfaction with their forecast accuracy and identifying factors which are most likely to lead to improved accuracy in the future.

3.4.1 Importance of collaboration

Firm's own assessment of the value of collaboration provides an interesting set of results. We asked respondents to rate the importance of each form of CIS on a five-point scale as in the following question:

Q20: Which of the forms of CIS have been important in improving forecast accuracy?

- Not Important
- Slightly Important
- Fairly Important
- Highly Important
- Critical

The question was only posed for the types of collaboration the firm was involved in so a firm only participating in S&OP was not asked how important VMI was to their forecast accuracy. The results to Q20 are presented in figure 20.

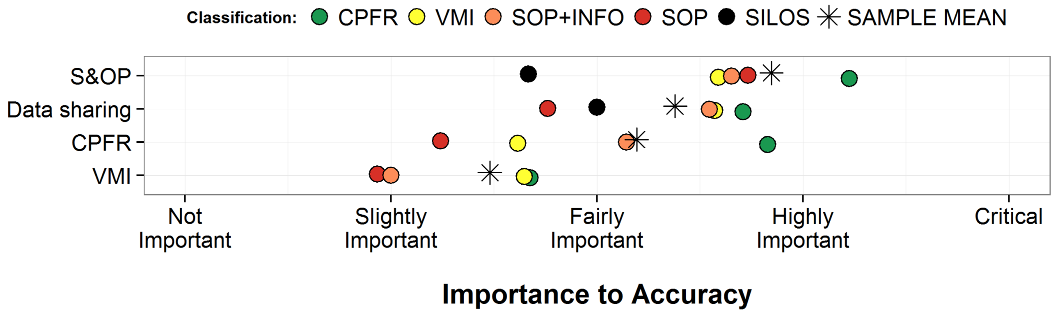

Figure 20: Importance of collaboration.

We will focus initially on the sample mean and the relative importance of the different types of collaboration to forecast accuracy. Figure 20 shows that S&OP is rated as the most important form of collaboration practiced. Second most important is data sharing, however it is possible that respondents have treated this as a general importance of data sharing rather than the importance of non-CPFR, non-VMI data exchange partnerships. Third most important was CPFR and finally VMI was deemed the least important collaborative scheme for improving forecast accuracy.

We see a consistent pattern in the relative importance of the collaboration types for each classification. In general, the ranking S&OP ← Data Sharing ← VMI ← CPFR is the same for each classification. The order is the same for S&OP (red) and SOP+INFO (orange), with VMI (yellow) and CPFR (green) only slightly out of synch.

Looking at the horizontal spread of the points for each line, we see the CPFR group out in front for all four types. This group rates S&OP and CPFR as being far more important to accuracy than the rest of respondents. It is to be expected that the S&OP and SILOS groups will be below the sample mean as they have a lesser involvement in the external forms of collaboration.

3.4.2 Importance of data in forecasting

In this section we will analyse which data is important to forecasters, presenting importance ratings for the 11 types of internal and 13 types of external data. The survey only asked respondents to rate the importance of data if they had previously said that they have it available and also use it in forecasting. It was assumed that because the forecaster did not use a specific type of data, they would not be able to judge its importance. Respondents were asked the following question:

Q21: How important are different types of internal data to your forecast accuracy?

Each data type was rated on a five-point scale as shown below:

- Not Important
- Slightly Important
- Fairly Important
- Highly Important
- Critical

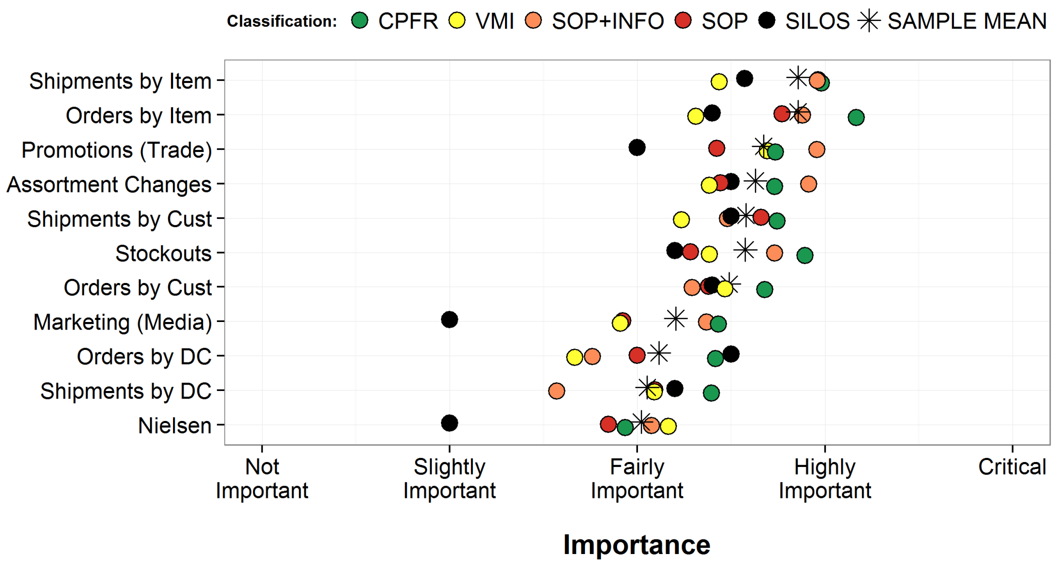

Figure 21: Importance of internal data to forecast accuracy.

The importance of different forms of internal data are compared in figure 21. Due to the sample mean being in the right half of the chart for each data type, it is shown that data is, on average, at least 'Fairly Important' to those who use it in forecasting.

Ranking the data types based on the sample mean, we see that orders and shipments by item and assortment changes are the most important data types. These time series form the backbone of the forecasting task as they are commonly used to develop a baseline statistical forecast. The next most important are promotional and assortment change data. We see that more granular orders and shipments data are less important to forecasters, unsurprising as we have seen that many do not forecast at this level. Marketing and Nielsen are ranked the least important in the list, along with transactional data at the DC level.

The importance of external data in forecasting is evaluated in the next question. Prior literature credits external data as being important to forecast accuracy. Our study will drill into the importance at a detailed level with 13 data types covered.

Q22: How important to forecast accuracy is the data provided by your customers?

As was the case with internal data, we only obtained a response where a particular data type is both available and used in forecasting. The responses were measured on the same scale as previously in Q21 (importance of internal data).

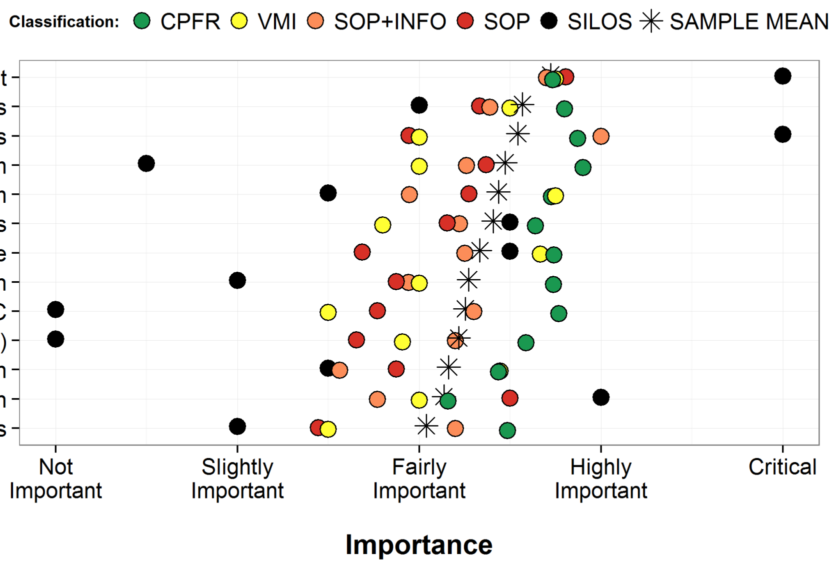

Figure 22: Importance of external data in forecasting.

Figure 22 shows how forecasters rate the importance of data shared by downstream partners. The sample mean for all data types is plotted in the right half of the chart, with all data types rated between 'Fairly Important' and 'Highly Important'. The most data types are promotions by account, listings/delistings, EPOS Sales and the two types of forecast data by item.

Looking at promotions by account, the points are clustered closely together around the sample mean. The SILOS response is based on two responses only and can be discounted. This tight clustering shows that promotional information is universally a highly important type of data.

This tight clustering is not repeated for the other data types and the points are more widely spread. Examining the distribution and ordering between the points, the CPFR group are clearly ahead of the average for the majority of data types. The importance ranking of certain data types varies considerably from the ranking of the sample mean values for CPFR. CPFR companies rank sales forecast by item and EPOS sales as the two most important data types, above the value for promotions by account.

We also see less importance attached to more granular data. Sales and order forecasts and promotions at the location level of detail are less important than the same information aggregated to the customer level. This again indicates that this level of detail is too great for firms who forecast at the customer and item level.

The number of respondents in the SILOS group is very small. Only 7 responses are classified as SILOS and these companies use very little external data in forecasting. As a result, some of the averages are based on only one or two responses.

As a final analysis based on the importance of data, we have further aggregated the data types to a higher level to compare overall internal and external data importance. At the higher level of reporting it is easier to observe the patterns and differences between the CIS groups. The analysis is shown in Figure 23

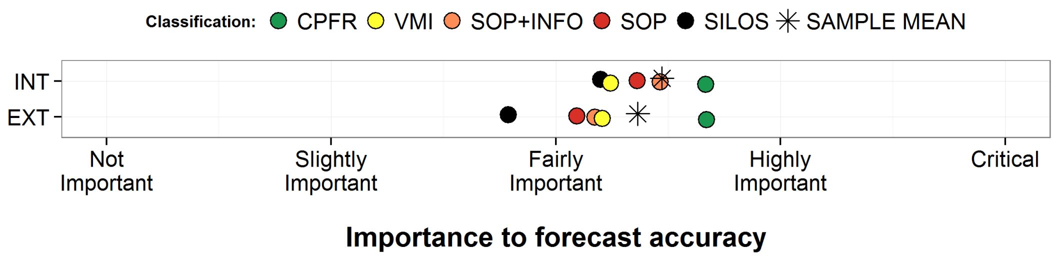

Figure 23: Relative importance of internal and external data in forecasting.

Key take-away point: there is minimal difference between the importance of internal and external data overall but the CPFR group place a higher importance on data than other less collaborative groups.

3.4.3 Satisfaction with Accuracy

The best measures of forecasting performance are actual forecast error or accuracy. The error statistics reported by respondents require further cleansing and review before publication. This is primarily due to the fact that respondents appear to have mistaken error and accuracy when completing this section. As a result the error metrics will be presented in a follow-up report.

We asked forecasters to self-assess their performance by telling us how satisfied they are with forecast accuracy. The actual question asked and options available are as follows:

Q23: How satisfied are you with forecast accuracy?

- Not at all satisfied
- Slightly satisfied
- Moderately satisfied
- Very satisfied
- Completely satisfied

The results of this question are plotted in figure 24.

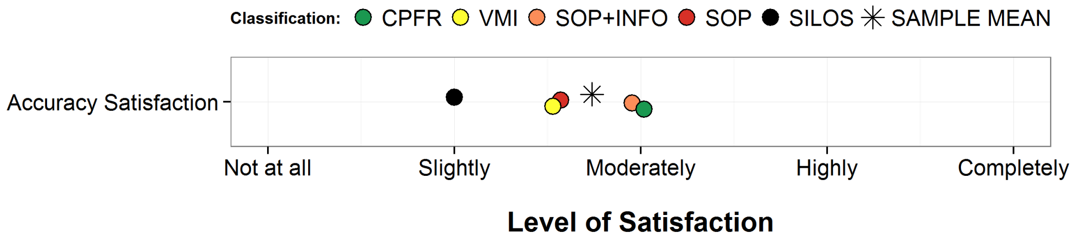

Figure 24: Satisfaction with accuracy.

The sample mean is below the midpoint, indicating that firms are less than 'Moderately Satisfied'. The classifications most engaged in external data-sharing, namely CPFR and S&OP+INFO, are more satisfied than the other groups.

3.4.4 Wishlist of factors

The final question covered in this report asks forecasters to identify which factors would help drive improved forecasting performance in the future. Respondents were provided with seven specific factors which could lead to accuracy gains. They were asked to select only those they deemed important and place them in order of importance within a list. The options available were as follows:

- More data provided by customers
- Closer collaboration with customers
- Automated integration of downstream data
- Better training for forecasters
- More staff to perform the task
- Better internal processes (e.g. S&OP)
- Better forecasting software

Q24: Which of these factors would most help you to improve accuracy? (select only the relevant answers in order of importance)

Respondents ranked the factors according to their individual needs and only selected relevant factors. The responses were transformed to a consistent scale representing Factor Importance using the following logic:

- Unselected factors score zero
- Selected factors: if rank = 1 then score = 7; if rank = 2 then score = 6

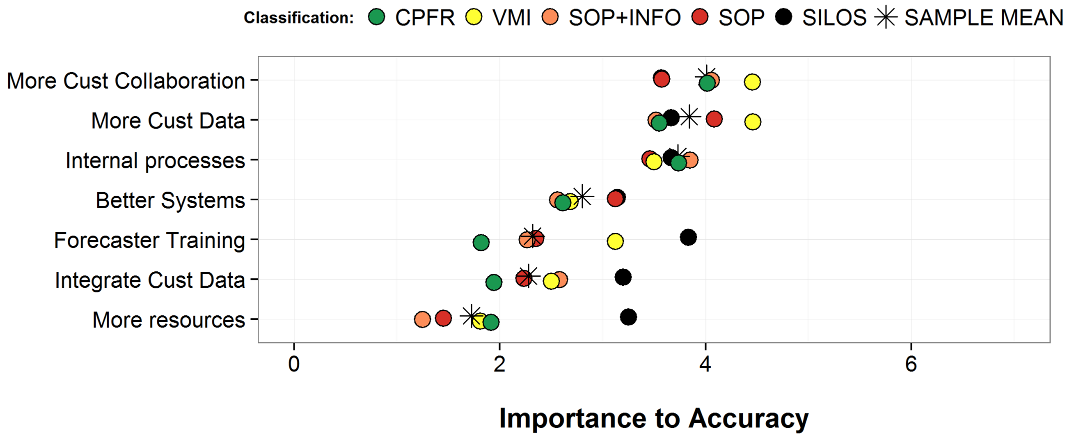

Figure 25: Factors which are important to accuracy in future.

In the rankings of importance for the different factors shown in Figure 25, the most important factors were more customer collaboration (average score = 4.0) and more customer data-sharing (3.8). Better internal processes was ranked as the third most important factor (3.7) in future forecasting accuracy improvements, only just behind the leading two. Other factors which ranked lower include better systems (2.8), better training (2.3), better integration of customer data (2.3) and more staff (1.8).

4 Conclusions

The manufacturers in our sample show that internal collaboration in the form of S&OP is highly practised and is augmented with a range of external CIS partnerships with retailers and distributors. These partnerships result in information flow upstream in the supply chain. Respondents indicate satisfaction with CIS partnerships and that they help to improve forecast accuracy.

Respondents indicate that judgement and statistics are fairly equally applied in forecasting. Despite advances in forecasting methods and the software available, judgement is still used in 70% of forecasts. Judgement in forecasting can suffer from bias and inefficiency. Research has shown that over-reliance on judgement can have negative impact on accuracy and that statistical methods can outperform judgement.

Given that information exchanged is typically unstructured in nature and that collaborative data is not consistent between trading partners, it easy easy to understand why forecasters tend to used information in a more unstructured, judgemental way.

With regards to the use of statistical methods, firms report that simple univariate methods prevail. Advanced methods capable of including causal and other exogenous variables are used less than 13% of the time. As prior research has shown, advanced statistical models can out perform univariate methods, especially where promotional intensity and uncertainty are high. This poses the question as to why forecasters do not take advantage of these techniques to improve baseline (prior to judgemental adjustment) forecast accuracy.

The types of software most frequently used by forecasters often lack the capabilities to use advanced statistical algorithms in time series forecasting. Issues regarding reliability and scalability make spreadsheets unsuitable to large-scale multivariate. In addition, many of the forecasting modules in ERP/MRP vendors' solutions lack advanced modelling capabilities and offer a limited range of models based around exponential smoothing and its seasonal and trended variants.

Software able to deal with the real world complexity of the forecasting task is seldom used. Specialist/stand-alone packages with additional modelling capabilities are ranked the most satisfactory by practitioners, however they are rarely used. We believe that mainstream software vendors should improve their functionality to include additional modelling capabilities and other features found in best-in-class software packages. Such features include:

- enhanced statistical modelling and optimised model selection routines
- management by exception and resolution workflow
- error metrics and KPIs
- hierarchical capabilities for different levels of the supply chain and multiple time buckets
- tools for managing promotions
- simple but controlled environment for making judgemental adjustments including reasons
- collaborative multi-user model

Collaboration on a large scale can consist of multiple trading partners sharing multiple types of data on a detailed level. Retail-level data can amount to several GB of data on a daily or weekly basis. It is therefore necessary to structure the data in a format suited to the needs of the forecaster. Research has stressed the importance of integrating external data smoothly. Our sample indicated, in general, that external data is easy to integrate into forecasting. Whilst this may be true when considering the use of judgement, firms have found it more challenging to integrate external data into their statistical forecasting.

In this area it should be noted that a new technology has emerged. Demand Signal Repositories, or DSRs, are data warehouses which enable manufacturers to store highly granular retailer data. They are able to store consumption at store level (POS Data), identifier mappings and changes, and other additional product-related information. These databases are used to support a range of applications including forecasting, promotions optimization, product mix choices and store-level planograms. We can provide links to additional reading in this area if required.

5 Future Directions & Next Steps

We believe the topic of forecasting under collaboration remains open and further research is required. We plan to undertake further analysis of the data collected, provide additional insight to respondents whilst enriching the data through cleansing and follow-up interview with participants. Some of these tasks will take place in parallel and a summary is provided below.

1. Follow-up report customised for each respondent

   To allow companies to benchmark themselves against their peers, we will generate a customer report comparing your response against the sample mean, industry sector mean and the collaborative leaders and laggards group scores.

2. Further data-cleansing and reliability checking

   Reliability will be tested for several questions. In particular, accuracy benchmarks are sparsely populated and certain respondents appear to have mistaken MAPE with accuracy, providing MAPE values in excess of 90%. The questions regarding firms' collaborative set-up in detail (e.g. number of customers, percentage of turnover, DC or POS-level) have also been answered in an unreliable manner in many cases.

   We hope to follow up with participants and allow them to correct any errors they may have made in their responses, particularly in the areas of accuracy and collaborative set-up. There will be an opportunity for respondents to update any other values in their survey where they may have misunderstood the question. The process of update will be limited to items where a clear error has been made.

3. Statistical analysis of the data to test specific hypotheses

   The exploratory phase of data analysis has identified certain interesting patterns in the data. Further hypothesis development is required in conjunction with statistical testing to support our findings.

4. Follow-up interviews with practitioners

   There are a number of areas where further detail and clarification is required to understand forecasting practice in the firms participating.

5. Collaboration seminar in London & possible follow-up workshop with UK-based forecasters

   Lancaster Centre for Forecasting are holding a seminar in January/February to present the results and bring together speakers with significant experience of this area in practice. Speakers are currently being recruited and a date will be provided shortly. The seminar will be a half-day in London and will feature a round-table discussion at the end. All participants of the study are invited to attend or send a representative from their organisation.

6. Investigate pan-organisational variations in CIS and forecasting

   In 2011 we pre-tested this survey with 20 forecasters from a global consumer goods company. Whilst the company as a whole was not highly engaged in CIS, it was interesting to note variation in practice between business units and countries.

   We are interested in running a similar study with companies to understand differences in forecasting within their organisations. The current survey can be tweaked to allow multiple responses from the same company with a unique survey code and custom reports can then be generated.

7. Modelling study to compare forecasting techniques under various collaborative schemes, data conditions and supply chain configurations

   The next major stage of the research will concern testing which forecasting algorithms work best under alternative supply chain configuration and CIS scenarios. The modelling will be based on simulated demand data which exhibits real-world influences such as promotions and assortment changes.

   We may also seek to work with firms using their own data to examine how forecast accuracy can be improved in our model with downstream data.

6 About the Authors

6.1 Matt Weller

Matt Weller is a PhD Candidate in Management Science at Lancaster University Management School. Prior to joining LCF, Matt worked in industry for 10 years as an IT consultant and has implemented planning solutions in several blue chip companies.

Matt's research focuses on how manufacturers of fast moving consumer goods (FMCG) are forecasting in the supply chain under new schemes of information sharing and collaboration. A first area of original research examines empirically how firms are currently combining collaboration and forecasting in practice. Next, this insight will be used to derive recommendations for the use of different statistical forecasting methods under alternative supply chain configurations, information exchange regimes, and demand data properties.

He has presented at the International Symposium for Forecasting 2011 in Prague, and 2012 in Boston, USA, and multiple doctoral symposia.

6.2 Sven Crone

Dr. Sven F. Crone is the director of the Lancaster Centre for Forecasting, and works as an Assistant Professor at Lancaster University Management School, UK. Sven has an MBA and PhD in forecasting for inventory management, and has published widely in esteemed journals.

In addition, Sven has over 15 years of expertise in corporate business forecasting, in particular in supply chain forecasting for FMCG manufacturers. His expertise includes improving software systems such as SAP APO-DP, e.g. by improving automatic statistical model selection, tuning ERP and forecasting systems for optimal performance, to developing bespoke forecasting methods for company specific products and markets. He regularly consults on structuring demand planning processes with assortment segmentation (ABC-XYZ), developing key performance indicators, and tactical planning. In addition to FMCG, he has supported companies along the supply chain, including raw materials producers and retailers, to provide a holistic understanding of SCM..

Sven has presented the Centre's innovations and projects at 50+ international conferences, including keynotes at the SAS F2006 & F2008 forecasting and A2012 Analytics conferences, track speeches at APICS 2006 global conference, and annual appearances at IBF and ISF conferences. He frequently provides training courses for the centre, IBF and IEEE, educating over 400 demand planners on Forecasting Fundamentals, Statistical Forecasting with SAP APO-DP and Forecasting with Neural Networks all over the world.

6.3 Robert Fildes

Robert is Distinguished Professor of Management Science in the School of Management, Lancaster University and Director of the Lancaster Centre for Forecasting. He was co-founder in 1981 of the Journal of Forecasting and in l985 of the International Journal of Forecasting. He has consulted and lectured widely on all aspects of the problem of improving forecasting in organisations. His major concern is that despite all the research companies still stay with old-fashioned systems and methods. The solution, he thinks, is better designed forecasting systems and better trained forecasters.

7 Appendix A

7.1 Overview of Sample

The research has been carried out through an online survey, which ran between January and August 2012. Invitations were extended via 2000 private LinkedIn messages to forecasters and supply chain professionals. Potential respondents were identified through their LinkedIn group memberships and job title. In addition we posted multiple times to relevant LinkedIn Groups, reaching a potential audience of more than 20,000 group members.

The survey instrument was piloted in 2011 and subsequently purified and pre-tested with global forecasters of a consumer goods manufacturer. Of the 280 completed responses, 15 were unusable due to:

- Consultants/academics
- Rushed surveys (10-15 mins)
- Very inconsistent answers
- Middle-clicking – same answer for every question in groups

In addition, there were 260 incomplete responses after multiple reminders. Most of there were only slightly complete. The reasons for this high number of incompletions was thought to be:

- Speculative interest only
- Unwilling to give email address (though not mandatory)
- Atrophy (number of repeated questions)
- Not a suitable respondent (industry sector & position)

The final sample of 200 manufacturers consisted mainly of demand planners & forecasters (including managers & directors). 87% of companies in the sample were larger than $100m annual turnover and the majority were from the consumer packaged goods (CPG) sector. The following plots show the sample breakdown by company size and industry sector.

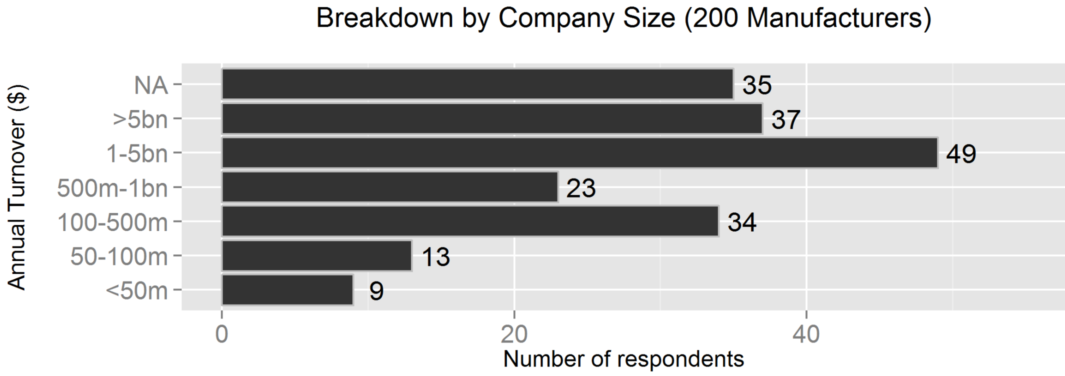

Figure 26: Sample breakdown by company size.

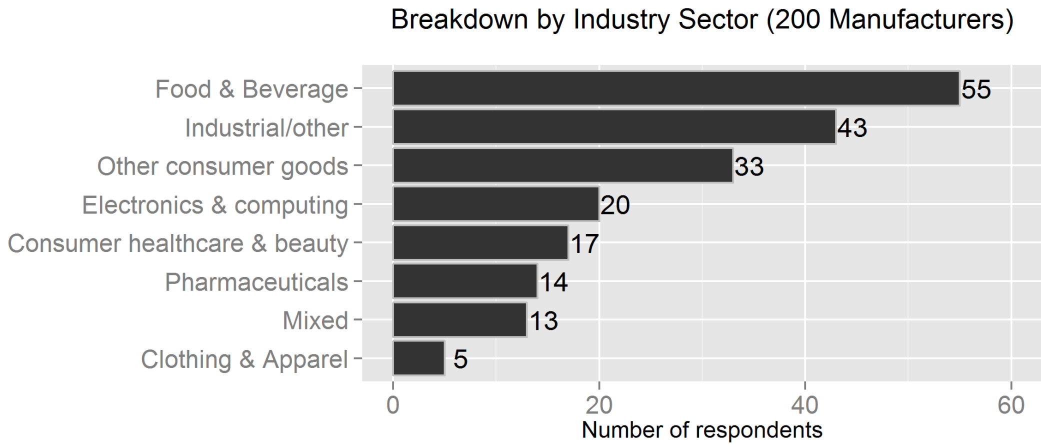

Figure 27: Sample breakdown by industry sector.

7.2 Classification & Grouping Approach

To simplify reporting and draw clear contrasts between the differing types of collaboration and hence collaborative maturity we devised a single classification algorithm. The classification process analyses the levels of CPFR, VMI, INFO and S&OP to identify key patterns. The logic only classified responses which clearly fitted one of the defined groups more than any other. In this process only 150 of the 200 responses can be clearly classified. The breakdown can be found in Figure 6. It is worth noting that many firms who were allocated to the CPFR grouping were also heavily involved in VMI, other information-sharing partnerships and S&OP. Because CPFR is the most advanced stage of collaborative forecasting it was deemed acceptable to group them under CPFR.

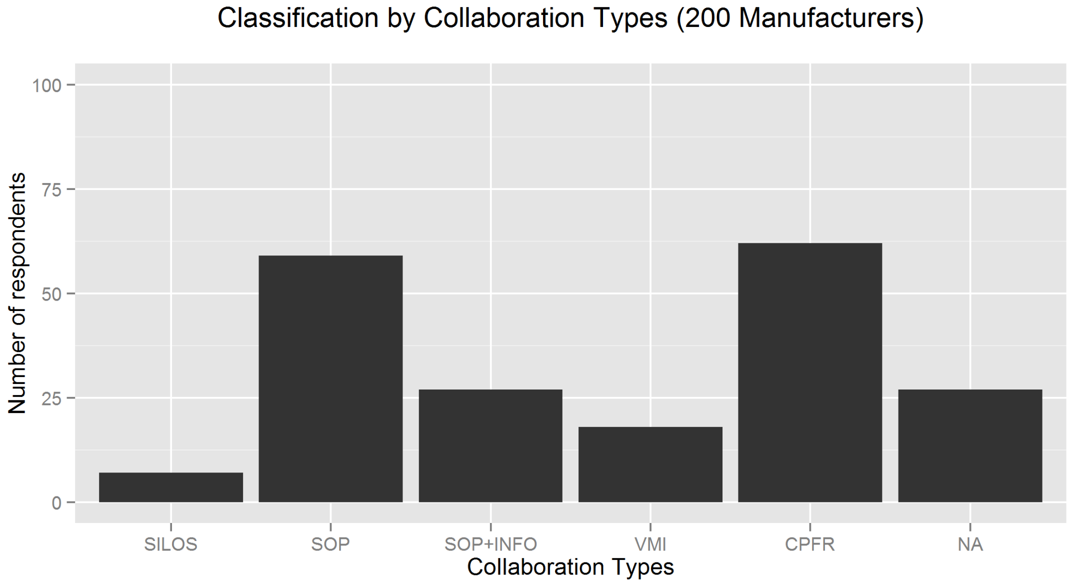

Figure 28: Collaborative classification plot.

In additional analysis, each response was grouped as a leader (LEAD), laggard (LAG) or mid-range (MID) for each of the types of collaboration investigated. Hence a response may be a CPFR leader but a VMI laggard because they always do CPFR and never VMI. In the Appendix we have produced a full set of charts for the leader versus laggard plots for each of CPFR, VMI, INFO, S&OP and total external collaboration (0-12 scale). The additional analysis is available upon request.