DEMAND FORECASTING PRACTICES AND PERFORMANCE: EVIDENCE FROM THE GMRG DATABASE

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Abstract

Several operations decisions are based on proper forecasts of future demand. For this reason, manufacturing companies consider forecasting a crucial process for effectively guiding several activities, and research has devoted particular attention to this issue. This paper investigates the impact of how forecasting is conducted on forecast accuracy and operational performance (i.e. cost and delivery performance). Attention is here paid on three factors that characterize the forecasting process: whether structured techniques are adopted, whether information from different sources is collected to elaborate the forecast, and the extent to which forecasting is used to support decision-making processes. Analyses are conducted by means of data provided by the fourth edition of the Global Manufacturing Research Group survey. Data was collected from 503 companies belonging to several manufacturing industries from eleven different countries. Results confirm the importance of leveraging, not only on forecasting techniques, but also on how the forecasting process is managed and organized to improve forecast accuracy. However, research findings show that companies adopting a structured forecasting process improve their operational performance not merely because forecast accuracy increases. This paper highlights the importance of designing the forecasting process coherently with how users intend to exploit forecast results and the aim that should be achieved, which is not necessarily that of improving forecast accuracy.

Keywords*:* Demand forecasting, Forecast performance, Forecast accuracy, GMRG

1. INTRODUCTION

Demand forecasting is an important issue for manufacturing companies. Several decision making processes need accurate forecasts in order to choose proper actions relevant to production planning, sales budgeting, new product launches, promotion planning, etc. For this reason, over the years, practitioners and academics have devoted particular attention to how forecasting can be improved to increase forecast accuracy (Wright et al, 1986; Armstrong, 2001; Caniato et al., 2002a, 2002b).

The adoption of structured forecasting techniques has been studied by several authors (Mentzer and Cox, 1984; Dalrymple, 1987, Sanders and Manrodt, 1994; Sanders and Ritzman, 2001). We refer to the use of quantitative (such as exponential smoothing or regression) and/or qualitative approaches (such as the Delphi method, panel of experts, etc.), rather than naïve methods, to elaborate sales forecasts (see section 4.2). Despite the plethora of studies on this issue, debate is still open on whether the adoption of structured forecasting techniques is always beneficial in improving forecast accuracy. In particular, during the last decade, several authors have challenged the assumption that: 'the greater the adoption of complex forecasting techniques – the better the forecast accuracy'. For instance, many authors attempted to demonstrate that the efficacy of forecasting techniques in improving forecast accuracy depends on the fit between the type of technique adopted and the context (Wright et al., 1996; Makridakis et al., 1998; Sanders and Manrodt, 2003). Moreover, several researchers suggested that forecasting technique adoption is not enough to guarantee good forecast accuracy (Armstrong, 1987; Mentzer and Bienstock, 1998; Moon et al., 2003). Forecasting management is a complex issue, that includes decisions on information-gathering processes and tools (e.g., what information should be collected, how it should be collected), organizational approaches to be adopted (e.g., who should be in charge of forecasting, and what roles should be designed), interfunctional and intercompany collaboration for developing a shared forecast (e.g., using different sources of information within the company or supply network, joint elaboration of forecasts, etc.), and measurement of accuracy (e.g., using the proper metric and defining proper incentive mechanisms). Adopting a structured forecasting technique could lead to no improvements in forecast accuracy, if information gathering or forecasting organizational approaches are not properly designed and managed. Thus, companies could decide to act on these levers to improve forecast accuracy, rather than investing in the implementation of new and complex forecasting techniques. It can be argued that the understanding of how improving forecasting to minimize forecast error requires studying not only the relationship between structured forecasting techniques and forecast accuracy, but also the impact of other forecasting levers linked to how the forecasting process should be designed and managed.

Improving forecast accuracy is often considered a necessity because large forecast errors usually negatively affect companies' operational performance, especially cost and delivery performance (Vollmann et al., 1992, Ritzman and King, 1993; Enns, 2002; Zhao and Xie, 2002; Kalchschmidt et al., 2003). This suggests that improving the forecasting process has a positive indirect effect on operational performance through forecast accuracy improvements. However, recent studies support that this is not the only relevant effect and that forecast accuracy is just one of the reasons that lead companies to improve the forecasting process (Barratt and Oliveira, 2001; Småros, 2007). In fact, a more structured forecasting process gives companies the opportunity to better understand market dynamics and customers' behaviours, reduce uncertainty on future events, and provide the company's functions with useful analyses and information. In turn, this can influence cost and delivery performance. This means that a better forecasting process does not lead to an improved cost and delivery performance, simply because forecast accuracy improves, since forecasting variables can directly affect these performance measures. Despite this, studies investigating this effect are few and far between.

The aim of this paper is twofold. Firstly, it intends to analyze the impact of how forecasting is conducted (i.e. the extent of use of structured forecasting techniques, several sources of information and forecast-based decision making) on forecast accuracy. Secondly, it aims to study the possible direct relationship between how forecasting is conducted and cost and delivery performance.

From a theoretical point of view, this research intends to contribute to existing literature in different ways. First of all, it analyzes not only the impact of using structured forecasting techniques on forecast accuracy and cost and delivery performance, but also the impact of how the forecasting process is organized and managed. In this way, this research intends to further support the literature on forecasting which suggests that the forecasting process should be analyzed in a comprehensive way and forecasting techniques are not the only relevant variables to be studied (Mentzer and Bienstock, 1998).

In addition, starting from an original premise, this research intends to prove that a direct relationship can exist between forecasting variables and cost and delivery performance. Quantitative research proving this effect is lacking.

From a managerial point of view, it is useful to know whether forecasting process variables are related, not only with forecast accuracy, but also directly with delivery and cost performance. A company may not be interested in improving forecast accuracy, as it does not consider this improvement a priority. However, through a better forecasting management, it could achieve important improvements in cost and delivery performance, by guiding company's decisions on the basis of a better understanding of market dynamics and customers' behaviour.

The remainder of the paper is structured as follows. In the next section literature on the effect of forecasting on companies' performance will be analyzed. Research hypotheses then follow. Section 4 will describe the research methodology adopted and section 5 will present the empirical results found. The following section will introduce the discussion of the research findings. In the end, the conclusions will discuss the main theoretical and managerial contributions of this study and highlight future research developments.

2. RESEARCH BACKGROUND

Literature regarding the impact of forecasting on companies' performance has devoted significant attention to forecast accuracy and its role. The effect of forecast error on manufacturing systems has been understood since the earliest works on production planning and control (Holt et al., 1955). Inaccuracies in forecasting can mean excess inventories or lost sales and can lead to severe cost impacts on manufacturing systems (Biggs and Campion, 1982; Lee and Adam, 1986; Vollmann et al., 1992; Ritzman and King, 1993; Ho and Ireland, 1998). Therefore it is no surprise that several surveys show accuracy as the most important criterion in selecting a forecasting approach (Dalrymple, 1987; Mahmoud et al., 1988). Forecast inaccuracy causes major rescheduling and cost difficulties for manufacturing (Ebert and Lee, 1995) and may impact on logistic performance, such as delivery timeliness and quality (Kalchschmidt and Zotteri, 2007). For this reason some authors have even recommended getting rid of forecasts altogether (Goddard, 1989).

Most firms attempt to improve forecast accuracy by focusing their efforts in different directions, mainly on forecasting techniques and procedures.

However, conflicting evidence is found on the relationship between the adoption of forecasting techniques and accuracy (Peterson, 1990; Mentzer and Kahn, 1995; Wacker and Sprague, 1998). A vast debate is ongoing regarding the efficacy of quantitative approaches (such as exponential smoothing or regression) and qualitative approaches (such as the Delphi method, panel of experts, etc.). Sanders and Manrodt (2003) provide a review of the contributions to this debate. Even though the discussion is still open, what seems to be important is using the right approach for the right problem: judgmental approaches appear to be preferable when demand is highly variable and affected by special events such as promotional activities, and when few historical data is provided. On the contrary, quantitative approaches are preferable when several forecasts need to be produced (i.e., for numerous products, or with frequent updates), good quality data is available and demand is rather stable (Wright et al, 1996; Makridakis et al., 1998). Integrating quantitative and judgmental approaches has also been suggested (Sanders and Ritzman, 2001; Franses and Legerstee, 2009). Fildes et al. (2009), for instance, highlight how to use qualitative methods to adjust statistical forecasts in order to improve forecast accuracy.

A further explanation of the non-unanimous results on the relationship between the adoption of forecasting techniques and forecast accuracy is that many firms, especially in commercial settings, face asymmetric risks when formulating forecasts, since the cost of a lost sale can greatly overcome the holding cost of the same product (Sanders, 2009). As Granger's (1969) study demonstrates, such considerations might cause an "optimal" forecast to deviate significantly from a least-mean-percentage-error prediction.

Finally, a relevant research stream on forecasting claims that forecasting techniques are not sufficient to improve forecast accuracy, if they are not accompanied by proper specific procedures and structured approaches for managing the forecasting process (Armstrong, 1987; Mentzer and Bienstock, 1998; Moon et al., 2003). Information sharing, for instance, is considered a relevant topic. Combining information and data from different functions within the company, and from suppliers and customers provides more knowledge regarding what future demand will be and how the future trend could change, and therefore this may be related to better accuracy (Kekre et al., 1990; Fisher et al., 1994; Bartezzaghi and Verganti, 1995; Chen et al., 2000). In addition, a structured approach to forecasting requires that forecasts are used within a company to support different decisions and processes, such as sales and budget preparation, production planning or new product development. In other words, all the decisions within a company, and even within a supply network, should be based on a shared forecast (Mentzer and Bienstock, 1998).

Evidence shows that the more companies tend to use structured approaches for forecasting demand, the more their performance improves (Fildes and Hastings, 1994; Mentzer, 1999). Interestingly enough, the use of a structured forecasting process may have significant impact on companies' performance and not only because forecast accuracy increases. Using systematic data collection from different sources to elaborate the forecast, together with appropriate data analyses, may be beneficial since it provides other functions with better information and offers the possibility of creating and diffusing a better understanding of market dynamics within the company. Again, the use of a vast information base reduces uncertainty on future events and, as a consequence, may be helpful in defining hedging actions that impact on cost and delivery performance (e.g., better use of slacks, better aggregate planning of production, etc.). In addition, the achievement of shared and agreed forecasts can help to establish proper objectives for salespeople and production units. Thus having a structured forecasting process may be useful not only for improving forecast accuracy, but also because this can have a direct influence on cost and delivery performance (Mentzer, 1994; Mentzer and Kent, 1999).

As a result, the forecasting process has changed its role over time: if at first attention was mainly given to the quality of the forecast in terms of accuracy, now several companies consider forecasting an important process, useful not only for defining sales plans, but also for better managing product life cycles, promotions, or relationships with customers. Recent studies on new forecasting approaches, such as Collaborative Planning, Forecasting and Replenishment (CPFR) support this statement. CPFR is a method based on the exchange of specific and timely information between trading partners within the supply network to develop a single shared projection of demand (McCarthy and Golicic, 2002). Several authors (Barratt and Oliveira, 2001; Danese, 2007; Småros, 2007) and cases in the literature (VICS, 1998; ECR, 2001; 2002) demonstrate that CPFR is used also for managing promotions and new product launches. In particular, Småros (2007) analyses four cases of CPFR implementation and demonstrates that companies participate in CPFR projects for several different reasons, such as for example, accessing retailer's information on different customer profiles, or POS data before, during and after promotions. This way, companies can better understand their market and customers, in terms of needs and preferences; use forecasts proactively, thus managing marketing and sales efforts more efficiently. In some cases, actors explicitly declared that the aim of the CPFR project was not to improve forecast accuracy (Småros, 2007).

3. FORECASTING VARIABLES AND RESEARCH HYPOTHESES

In this section, we first describe the relevant forecasting variables under consideration and then formulate specific hypotheses to be tested.

3.1. Forecasting variables

Different elements constitute and characterize the forecasting process and some authors have proposed different frameworks of analysis. In the 80s, Armstrong (1987) considered a model based on four dimensions: forecasting methods (i.e., the kind and number of techniques used), data available (i.e., whether a central database is available which collects information from different sources), uncertainty analysis (i.e., upper and lower limits of forecast are provided), costs and benefits (i.e., amount spent on forecasting and performance achieved). Fildes and Hastings (1994), in a subsequent research, took into consideration three variables: the forecaster and decision maker (i.e., forecaster's training and use of forecasts for different decision making processes), information flows (i.e., using information on the environment) and the technical characteristics of the forecast (i.e., accuracy and bias). Mentzer and Bienstock (1998) divide forecasting management into four areas: the techniques that can be adopted to elaborate forecasts; forecasting systems that allow the forecaster access to a common information base within the company and use of data from customers and suppliers; managerial forecasting approaches that differ not only with regard to the extent to which data and information from different sources are used, but also the extent to which decisions within the company are based on a single forecast; and forecasting measurement, concerning the type of metric used to measure forecast accuracy and operational performance related to forecasting process. Finally, in a more recent study, Moon et al. (2003) propose a forecasting model composed of four dimensions: functional integration (i.e., degree of communication and coordination between functional areas), approach (i.e., the kind of technique used), systems (i.e., electronic links, information availability), and performance measurement (i.e., metric for accuracy).

Even though the terminology differs across the studies, it emerges that some variables recur as factors to leverage on in order to manage the forecasting process. In particular, three groups of variables describing how the forecasting process is conducted seem particularly important, and thus will be considered in this article: the *techniques* adopted, the *information* combined to elaborate forecasts and the *role* of forecasting in supporting decision making within the company. Measures used to characterize these variables are discussed in section 4.

Table 1 compares the variables considered by the abovementioned authors in their forecasting models, and classifies them into the three variables, labelled in this paper as techniques, information and role. A further variable in each model is linked to performance achieved. Forecast accuracy is often considered but some models take into account also other types of performance, such as operational performance. In this paper, forecast accuracy will be defined in terms of forecast error and will be measured by using the mean absolute percentage error (MAPE), which is a measure commonly used in the literature (Mentzer and Bienstock; 1998) (see section 4.2).

	Armstrong (1987)	*Fildes and Hastings (1994)*	*Mentzer and Bienstock (1998)*	*Moon et al. (2003)*
Techniques	Forecasting methods		Techniques	Approach
Information	Data available	Information flows	Forecasting systems	Systems
Role		Forecaster and decision maker	Forecasting managerial approaches	Functional integration
Other	Uncertainty analysis			
Performance	Costs and benefits	Technical characteristics of the forecast	Forecasting Measurement	Performance measurement

Table 1. Forecasting variables

3.2 Research hypotheses

For years, in the forecasting field, the primary purpose of researchers and practitioners has been to provide companies with sophisticated techniques able to produce accurate forecasts (Chase, 1999). However, the relationship between forecasting technique adoption and accuracy achieved is not straightforward. Lawrence et al. (2000), for instance, demonstrated that accuracy is not always higher when complex rather than naïve techniques are used. As previously discussed, this may be due to the efficacy of technique adoption in different contexts (Wright et al., 1996; Makridakis et al., 1998; Sanders and Manrodt, 2003) or to the use of an unstructured process (Wacker and Sprague, 1998; Kalchschmidt and Zotteri, 2007). However, several authors claim that using structured techniques is often helpful since it reduces judgmental bias and the effects of irrelevant information (Makridakis et al., 1998). In addition, combining qualitative and quantitative methods is usually very useful (Clemen and Winkler, 1986; Chase and Charles, 2000; Sanders and Ritzman, 2001). Therefore we formulate the following hypothesis:

H1: The use of structured techniques is negatively related to forecast error.

Many authors focus on the role of information in reducing forecast error (see section 2). Several contributions show that additional information from different functional areas (e.g., market plans), or from customers and suppliers can enhance knowledge of future events, thus allowing more accurate forecasts to be elaborated. Collecting information from different sources may be beneficial since forecasters can anticipate future customers' requests and better understand the value of each single piece of information (Fisher et al., 1994; Remus et al., 1995). Diebold (1989) maintains that pooling information, when it is possible and not prohibitively costly, is extremely useful. Therefore we can posit that:

H2: The use of several sources of information is negatively related to forecast error.

A key issue in understanding how the forecasting process can impact forecast error is also the role of forecasting itself within the company. Several companies use forecasting for production planning, sales budgeting, purchasing and planning long term investments (Wisner and Stanley, 1994; Klassen and Flores, 2001). The more decision making is forecast-based the more accuracy becomes relevant. In fact if the forecast is shared and used to support different processes, increasing forecast accuracy becomes very attractive (Wacker and Sprague, 1995; Mentzer and Khan, 1997; Mentzer and Bienstock, 1998; Moon and Mentzer, 1998). Thus, the following hypothesis is proposed:

H3: The extent of forecast-based decision making is negatively related to forecast error.

Forecast error is not important per se but it is a fundamental issue since it may affect operational performance. The literature provides evidence regarding this relationship, showing that a reduced forecast error improves the trade-off between inventory investments and service level (Kalchschmidt et al., 2003), and has significant cost impact on manufacturing systems (see section 2). Forecast errors typically affect cost and delivery performance. Inventory cost is frequently considered (Gardner, 1990; Fisher and Raman, 1996; Zhao and Xie, 2002), but some authors also take into account the impact on the overall manufacturing system, in terms of manufacturing costs (Biggs and Campion, 1982; Lee and Adam, 1986; Vollmann et al., 1992, Ritzman and King, 1993). First of all, an accurate forecast allows a better estimation of the short and long term capacity required. This, in turn, leads to better equipment utilization. Moreover, according to a looking-ahead perspective, by accurately forecasting future events, companies can better plan the actions to be undertaken (e.g., need for increasing capacity, outsourcing of production in certain periods, opportunity to produce products for other companies when demand is low, etc.).

Other authors have analyzed delivery performance showing that an accurate forecast can make the product available when the customer orders, thus reducing delivery and order fulfillment time and improving service level (Enns, 2002; Kalchschmidt et al., 2003). Also delivery punctuality could increase as, when products and components are available at the right time in the right quantity, the delivery date can be easily estimated.

This evidence suggests that forecasting variables can indirectly affect cost and delivery performance through forecast error. However, some cases in the literature demonstrate that companies do not always implement structured forecasting processes with the aim of reducing forecast error (Hughes, 2001; Kalchschmidt and Zotteri, 2005), and in turn improving cost and delivery performance. Firms sometimes pay significant attention to forecasting because this helps managerial processes, improves decision-making and thus operational performance directly (Winklhofer and Diamantopoulos, 2002). Companies, for example, can improve their promotion plans by better understanding the effect of their promotions on demand (Caniato et al., 2002a). In addition, managers may be able to better comprehend market dynamics, thus improving sales approaches. Again, companies may provide salespeople with better information regarding future trends in the market so as to improve their ability to raise margins and revenues, and to coordinate their actions accordingly. Unfortunately the literature does not provide evidence on this issue, and thus we intend to analyze the following hypotheses on the possible direct relationships between forecasting variables and operational performance.

H4a: The use of structured techniques has a positive direct effect on cost performance.

H4b: The use of structured techniques has a positive direct effect on delivery performance.

H5a: The use of several sources of information has a positive direct effect on cost performance.

H5b: The use of several sources of information has a positive direct effect on delivery performance.

H6a: Forecast-based decision making has a positive direct effect on cost performance.

H6b: Forecast-based decision making has a positive direct effect on delivery performance

Figure 1 shows the research model and hypotheses we intend to test. Each forecasting variable (i.e. techniques, information and role) is supposed to be negatively associated with forecast error (H1; H2 and H3, respectively), which in turn could affect cost and delivery performance. In addition, each forecasting variable could directly and positively affect cost (H5a; H6a; H7a) and delivery (H5b; H6b; H7b) performance. Figure 1 reveals the intention to prove that the relationship between the forecasting variables and cost and delivery performance is not completely explained by forecast error, because a direct effect exists between the forecasting variables and operational performance.

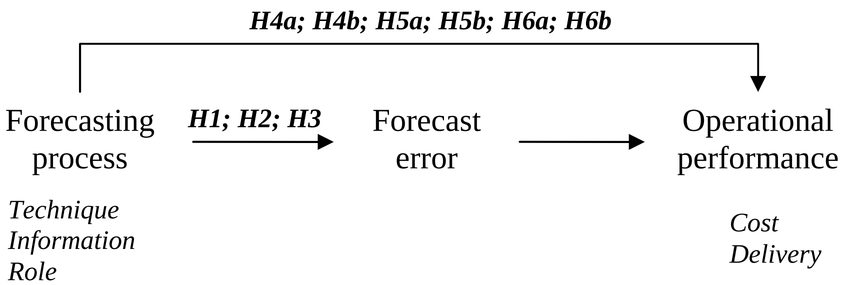

Figure 1. The theoretical model under investigation

4. RESEARCH METHODOLOGY

4.1 Sample description

Analyses are conducted by means of data collected by the Global Manufacturing Research Group (GMRG). The GMRG coordinates an extensive data gathering process regarding manufacturing practices in several countries from across the world. Data is available from 503 companies in 11 different countries. Table 2 provides the sample size from each country. The sample is distributed over different company sizes (see table 3) and industrial sectors all belonging to the manufacturing and assembly industry. The sample is mainly composed of medium-sized companies but also small and large ones are represented.

Country	**%**		**Country**	**%**
Albania	2,9		Macedonia	7,5
Austria	3,3		Mexico	20,1
Croatia	15,7		Poland	10,9
Hungary	10,2		Sweden	6,1
Ireland	7,1		Switzerland	5,9
Italy	10,3			

Table 2. The sample distribution over countries

Company size	**%**
Small (n. Employees < 50)	32,9%
Medium (n. Employees 50 - 250)	42,9%
Large (n. Employees > 50)	24,2%

Table 3. The sample distribution according to company size

Companies in the sample manage forecasting in different ways. Table 4 provides some descriptive statistics on the forecasting activity carried out by these companies.

	Mean	Median	Std. deviation	1st Quartile	3rd Quartile
Time horizon (months)	7.95	6.00	8.43	3.00	12.00
N° of forecast modifications in one year	9.49	4.00	31.13	2.00	12.00

Table 4. Descriptive statistics of the forecasting activity.

A vast majority of the sample (75% of the considered companies) develops forecasts over a time horizon which is less than 1 year and the median of the sample is 6 months. The number of forecast modifications over one year differs from company to company. Several firms update their forecasts less than once a month (3rd quartile is 12 times a year) but standard deviation is very high, showing that companies in the sample behave differently. This evidence proves that the considered sample includes very different behaviours and therefore the results presented in the next section should not be biased at least in terms of the nature of the forecasting activities.

4.2 Measures

Several items of the GRMG dataset were used in this study. We analyzed the extent to which the forecasting process is structured by means of three variables: the extent of use of forecasting *techniques*, extent of use of *information* from different sources, and the forecasting *role* in decision making.

In order to define the different constructs, principal component analysis (Varimax rotation) (Hair et al., 2006) and reliability verification were adopted. First, those items that could be related to specific constructs were selected and their correlation was verified. Then principal component analysis was applied by extracting all the eigenvalues above 1. When more than one factor was identified, Varimax rotation with Kaiser normalization was applied. Factor loads were verified in order to consider only items that have a factor load above the minimum requirement of 0.40 (Gefen et al., 2000). Reliability of the constructs was then checked by means of Cronbach's Alpha in order to prove that the value is above the minimum requirement of 0.60 (DeVellis, 1991; Nunnally, 1994).

To measure the extent to which structured techniques are used we asked respondents to indicate to what extent: (1) quantitative time series models (i.e. exponential smoothing), (2) quantitative causal models (i.e., regressions) and (3) qualitative models (i.e., market surveys)[*] were adopted to elaborate the forecast. These items are measured on a 7 point Likert scale ranging from 1 (not at all) to 7 (to a great extent). The three items are correlated with each other (all Pearson Correlation indexes are above 0.40 and are all significant at 0.01 level). A principal component analysis was conducted identifying that factor loads are all above 0.70 and that only one component is significant (total variance explained 63.1%). Cronbach's alpha is 0.70 confirming the reliability of the construct. Thus, in line with Wacker and Sprague's study (1995), the construct *Technique* is defined by averaging these three items.

Similarly, data on information used in the forecasting process was collected regarding the extent to which each of the following sources was considered: (1) current economic conditions, (2) customers' sales plans, (3) market research. These items are measured on a 7 point Likert scale ranging from 1 (not at all) to 7 (to a great extent). The three items are correlated with each other (all Pearson Correlation indexes are above 0.27 and are all significant at 0.01 level). The principal component analysis identifies that only one component is significant (total variance explained 51.1%) and factor loads are all above 0.7.

[*] For details on the questionnaire we refer to the GMRG website where a copy of the questionnaire can be downloaded: http://www.gmrg.org

Cronbach's alpha is 0.68. Therefore the construct *Information* is defined by averaging the three items.

In addition, data concerning the role of forecasting in decision making was collected, by asking respondents to indicate to what extent forecast is used for the following purposes: (1) sales and budget preparation, (2) production planning. These items are measured on a 7 point Likert scale ranging from 1 (not at all) to 7 (to a great extent). The two items are correlated with each other (all Pearson Correlation indexes are above 0.30 and are all significant at 0.01 level). The principal component analysis identifies that only one component is significant (total variance explained 55.4%) and factor loads are all above 0.70. Cronbach's alpha is 0.73. Thus the construct *Role* is defined by averaging the two items.

With regard to the performance variables, in this study, three types of performance were considered: *forecast error*, *cost* and *delivery* performance.

Several measures of forecasting accuracy exist; among these, one of the most common measures is the mean absolute percentage error (MAPE) (Mentzer and Bienstock; 1998). This is a measure used by several companies, and consistent with that employed by previous surveys (McHugh and Sparkes, 1983; Dalrymple, 1987; West, 1994). Therefore, in this study, MAPE was chosen to evaluate forecast accuracy. Coherently with Wacker and Sprague's study (1995), a two-item scale was created as the respondents were asked to indicate: (1) for an individual product, what percent would be the forecast error two months in the future, and (2) for the total sales, what percent would be the forecast error 24 months in the future. The two items are correlated with each other (Pearson Correlation index is 0.58 and significant at 0.01 level). The principal component analysis identifies that only one component is significant (total variance explained 79.2%) and factor loads are 0.89. Cronbach's alpha is 0.74. Thus the construct *Forecast Error* is defined by averaging the two items.

Although MAPE is a measure used in several surveys, it is also important to consider the potential weaknesses linked to it. As pointed out in section 2, in commercial settings companies face asymmetric risks when formulating forecasts, and as a consequence, an optimal forecast can deviate significantly from a least-mean-percentage-error prediction. Thus, in these cases, the MAPE may not be a good measure to distinguish between "bad" and "good" forecasts.

Moreover, forecast errors in sales forecasting seems to be a straightforward concept, but it gets a bit more complicated when we try to interpret it. It is a truism, for example, that the evaluation of whether the accuracy achieved is good or not depends on the context and, in particular, on demand. In a context where demand is not stable, a certain MAPE can be interpreted as an excellent result; while the same percentage, in a context where demand is steady can be deemed a poor result. Therefore, in this research, the variable "demand range" (*range*) will be measured and considered as a control variable influencing the relationships investigated. As in previous works (Frohlich and Westbrook, 2002; Zhu and Kraemer, 2002; Zhu et al., 2004), respondents were asked, given 100 as the average monthly demand, what are the highest and lowest monthly demands. Given these values, we defined the demand range as follows:

$$Range = \frac{Highest\ Monthly\ Demand - Lowest\ Monthly\ Demand}{100}$$

In the end, *cost* and *delivery* performance were considered. With regard to cost performance, three items were examined. We asked respondents to provide an evaluation of the following performance compared with their competitors on a 7 point Likert scale (1 for "far worse than" and 7 "far better than"): (1) direct manufacturing costs, (2) total product costs, (3) raw material costs. With regard to delivery performance, a similar question was asked for the following: (1) order fulfilment speed, (2) delivery speed and (3) delivery as promised. It can be noted that, since it is difficult to compare performance between companies operating within different contexts, this research focuses on perceptual and relative measures of cost and delivery performance. A principal component analysis was conducted identifying two factors: one related to cost performance and one regarding delivery. Factor loads are all above 0.80 and total variance explained is 77.5%. Cronbach's alpha is 0.79 for the cost construct and 0.90 for the delivery construct, confirming their reliability. Thus the constructs *Cost* and *Delivery* are defined by averaging the specific items.

In order to check for the validity of the cost- and delivery-performance constructs here defined, we verified their relationship with two quantitative measures related at least partially with these constructs. Cost performance is positively correlated with the percentage increase in labor productivity (Pearson correlation is 0.145 with $p < 0.05$), and delivery performance is negatively correlated with the percentage of late orders (Pearson correlation is -0.271 with $p < 0.001$). Although these relationships do not provide conclusive evidence on the quality of constructs, at least we can claim that the measures considered are able to grasp some of the variance in the sample.

Table 5 synthesizes the information regarding the constructs defined.

Construct	Average	Cronbach's Alpha	Item
Techniques	3.45	0.70	Quantitative time series models
			Quantitative causal models
			Qualitative models
Information	4.54	0.68	Current economic conditions
			Sales plan
			Market research
Role	4.77	0.73	Sales and budget preparation
			Production planning
Forecast error	18.2%	0.74	Short-term single product error
			Long-term aggregate error
Cost	4.42	0.79	Direct manufacturing costs
			Total product costs
			Raw material costs
Delivery	5.23	0.90	Order fulfillment speed
			Delivery speed
			Delivery as promised

Table 5. Details on research constructs

In addition to the variable range, in this study we also considered firm size (*size*), measured in terms of the natural logarithm of number of employees, as a control variable.

Moreover, we checked for industry- and country-specific effects. In order to assess whether industry and country could affect our results, we ran ANOVA analyses on the considered variables with industry and country as factors. Results show that there is no significant difference at 0.05 level among the considered industries, while countries show some statistically significant differences (sig. < 0.001). Therefore, in line with other studies (Bozarth et al., 2009), and in order to control for country effects, the items used were standardized by country. The result was that a particular plant's scores were scaled in relation to other respondents in the same country group. While we recognize that it could be interesting to study country differences with regard to forecasting management, the present research goal is to measure the impact of forecasting variables on forecast accuracy, cost and delivery performance. Future research could be directed at determining how the relationships posited in section 3 might differ across different countries. Thus, in the following analyses all constructs refer to the items standardized by country. Table 6 shows the correlations among all considered constructs and variables.

	Range	Cost perf.	Delivery perf.	F. error	Technique	Information	Role
Size	-.122**	0.148***	0.043	-0.134**	0.163***	0.286***	0.437***
Range		-0.087	0.040	0.228***	-0.044	-0.062	-0.101
Cost perf.			0.306***	-0.117***	0.170***	0.253***	0.226***
Delivery perf.				-0.053	0.240***	0.197***	0.199***
F. error					-0.073	-0.137**	-0.171***
Technique						0.458***	0.363***
Information							0.454***

Table 6 Correlations among constructs (sig. < 0.1, ** sig. < 0.05, *** sig. < 0.01)*

5. EMPIRICAL ANALYSIS

5.1. Impact of forecasting process variables on forecast error

We used multivariate analyses to test the hypotheses of relationship between forecasting variables and forecast accuracy (H1, H2,and H3). Three regression analyses were run, one for each forecasting process variable: techniques, information and role (Tables 7a, b, c). In these analyses, control variables (i.e. size and range) were also considered. Each step of the procedure was controlled for multicollinearity by checking the variance inflation factor. It is always lower than 1.5, and thus respects the suggested cut-off point of between 5 and 10 (Neter et al., 1989; Hair et al., 2006; Menard, 1995;). This suggests a low risk of multicollinearity.

a)

Variable	**Std. Coeff.**
Range	0.196***
Size	-0.078
Technique	-0.046
R^2 (adj R^2)	0.053 (0.042)***

b)

Variable	**Std. Coeff.**
Range	0.183***
Size	-0.074
Information	-0.091*
R^2 (adj R^2)	0.057 (0.046)***

c)

Variable	**Std. Coeff.**
Range	0.229***
Size	-0.009
Role	-0.151**
R^2 (adj R^2)	0.083 (0.073)***

Table 7. Results of regression analyses – Forecast error as dependent variable – a) Technique as regressor; b) Information as regressor; c) Role as regressor (sig. < 0.1, ** sig. < 0.05, *** sig. < 0.01).*

As it can be noted, there are significant and negative relations between forecast error and both information and role constructs. This confirms previous literature results that the more information is provided to the forecasting process the more accurate it is. Similarly, those companies that base their decision making on demand forecasting are also those where forecasts are more accurate. Thus we can claim that hypotheses **H2** and **H3** are supported. Moreover, as expected, in all the regression models forecast error depends also on demand range. On the contrary, the relation between forecast error and the use of structured techniques, even though it is negative as we anticipated, is not significant at 0.1 level. Thus we cannot affirm on the basis of the data in this survey that a relationship exists between these two variables, and thus this research does not support hypothesis **H1**.

5.2. Direct and mediated impact of forecasting variables on cost and delivery

The mediation effect of forecast error was analyzed according to the procedure suggested by Baron and Kenny (1986). Establishing mediation involves four steps (Baron and Kenny, 1986):

1. Step 1: verifying whether the initial variable (x) is significantly associated with the mediator (m).
2. Step 2: verifying whether the initial variable is significantly associated with the dependent variable (y).
3. Step 3: verifying whether the mediator is significantly associated with the dependent variable when the initial variable is also introduced into the equation.
4. Step 4: verifying whether the initial variable is significantly associated with the dependent variable when the mediator is also introduced into the equation.

In Tables 7 a, b and c, each forecasting variable is regressed on the forecast error, thus verifying the first step of this procedure. We can note that for the technique variable, this step is not verified, since it is not related to forecast error. We adopted a hierarchical regression analysis (Wampold and Freund, 1987) to verify the remaining steps (tables 8, 9 and 10). Firstly, control variables (i.e. firm size and range) were considered in the regression model with cost (or delivery) as the dependent variable. Then one forecasting variable (e.g. role) was inserted in the analysis, thus verifying step 2 of the mediation test. Finally, forecast error was added in the regression model, thus regressing cost (or delivery) on both the forecasting variable and the mediator forecast error.

Variable	Cost performance			Delivery performance		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	β	β	β	β	β	β
Range	-0.092	-0.085	-0.067	0.068	0.076	0.077
Size	0.149**	0.126*	0.120	0.035	-0.006	-0.007
Technique		0.162***	0.159***		0.263***	0.263***
Forecast error			-0.091			-0.008
R^2	0.034***	0.060***	0.068***	0.005	0.073***	0.073***
ΔR^2	0.034***	0.026***	0.008	0.005	0.068***	0.000
ΔR^2 adj	(0.026)	(0.023)	(0.004)	(-0.005)	(0.064)	(-0.005)

Table 8. Results of hierarchical regression – Forecasting technique (sig. < 0.1, ** sig. < 0.05, *** sig. < 0.01).*

Variable	Cost performance			Delivery performance		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	β	β	β	β	β	β
Range	-0.092	-0.077	-0.063	0.068	0.098	0.099
Size	0.149**	0.067	0.062	0.035	-0.015	-0.015
Information		0.259***	0.252***		0.175***	0.175***
Forecast error			-0.076			-0.003
R^2	0.034***	0.093***	0.098***	0.005	0.035**	0.035**
ΔR^2	0.034***	0.059***	0.005	0.005	0.037***	0.000
ΔR^2 adj	(0.026)	(0.058)	(0.002)	(-0.005)	(0.026)	(-0.005)

Table 9. Results of hierarchical regression – Information (sig. < 0.1, ** sig. < 0.05, *** sig. < 0.01).*

Variable	Cost performance			Delivery performance		
	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
	β	β	β	β	β	β
Range	-0.092	-0.092	0.077	0.068	0.042	0.043
Size	0.149**	0.038	0.038	0.035	-0.025	-0.025
Role		0.282***	0.272***		0.274***	0.272***
Forecast error			-0.065			-0.008
R^2	0.034***	0.105***	0.108***	0.005	0.082***	0.082***
ΔR^2	0.034***	0.071***	0.003	0.005	0.077***	0.000
ΔR^2 adj	(0.026)	(0.068)	(0.000)	(-0.005)	(0.073)	(-0.005)

Table 10. Results of hierarchical regression – Role (sig. < 0.1, ** sig. < 0.05, *** sig. < 0.01).*

Results show that all forecasting variables are significantly related with both cost and delivery performance. Quite interestingly in all regression analyses, forecast error is not statistically significant. This means that the existence of a mediation effect through forecast error is not supported, while there is a significant direct effect of each forecasting variable on cost and delivery performance. We further tested whether any mediation effect through forecast error could be found when considering the role and information variables, by applying the Sobel test (Sobel, 1982). For these two variables step 1 of Baron and Kenny's procedure was verified (tables 7b and c). Sobel (1982) provides a significance test for the indirect effect of the independent variable on the dependent variable via the mediator. The Sobel test further confirms that the mediation effect in all the regression analyses is not significant (Sig > 0.100). Thus, based on our survey data, we can conclude that each forecasting variable has a direct effect on operational performance which is not mediated by forecast error. Based on these results we can support hypotheses **H4**, **H5** and **H6**.

6. DISCUSSION

The previous analyses show that a significant forecast-error improvement can be achieved when companies lever on both information and role. However this research does not support the hypothesis that there is a clear relationship between forecasting techniques and accuracy. This result is consistent with previous findings that have shown that this relationship is not always verified. This may be due to the fact that the efficacy of forecasting techniques in improving forecast accuracy can vary in different contexts. Moreover, simply adopting structured techniques is not sufficient to obtain good forecast accuracy, but other actions are needed. Finally, a further explanation for the lack of a significant relation between forecasting techniques and forecast accuracy can be linked to the way forecast accuracy is measured in this study, i.e. through MAPE. As previously explained (sections 2 and 4.2), in some contexts, an optimal forecast could deviate significantly from a least-mean-percentage-error prediction, especially when companies face asymmetric risks because the cost of a lost sale greatly outweighs the holding cost of an item.

The analysis of the impact on operational performance shows something peculiar. First of all, the extent of the use of structured techniques and information from different sources, and the role of forecasting within the company are significantly related with cost performance. In particular, the existence of a mediated effect through forecast error is not supported. This suggests that adopting a more structured process not only helps to provide a better forecast, but also has a direct impact on cost performance. Adopting structured techniques can, for instance, limit the possibility of judgmental bias; whereas the adoption of a ‘single’ forecast to support different processes and decisions (i.e. role of forecasting) helps to align the activities and plans of various functional areas within the company. These conditions are crucial in order to avoid the spread of ‘islands of analysis’, in which each function elaborates and uses its own forecast (Mentzer and Bienstock, 1998). The consequent misalignment of plans and decisions usually causes an increase in production, distribution and inventory costs (Stevens, 1989).

Collecting information from different sources may also be beneficial, since it allows companies to better analyze and understand demand and markets – for instance identifying specific patterns or buying behaviours. The information and knowledge acquired can be used to improve customer relationships or supplier management. For instance, salespeople could decide to differentiate promotion plans across different clusters of customers or focus their efforts on developing strong relationships with a precise group of customers. Again, purchasing managers could decide to focus on specific material sources, by considering how the market will evolve with respect to existing and future products. Thus, collecting a wide range of data from different sources allows companies to provide functional areas with an in-depth demand analysis that may help to reduce uncertainty with regard to future events and define actions accordingly. This in turn can impact on company’s costs thanks, for example, to an efficient use of human resources, or a better management of supply chain relationships.

A similar result emerges when evaluating the impact of forecasting variables on delivery performance. All forecasting variables and the delivery performance are significantly related, and the existence of a mediation effect through forecast error is not supported. In companies where a structured forecasting process is adopted, sales policies can be influenced and guided by the forecasts elaborated. Salespeople can sometimes decide to influence (at least to a certain extent) customers’ preferences and direct customers’ choices towards products that are already available or what will be produced in accordance with forecast plans. Salespeople are obviously more motivated when forecasting process impacts on several important decisions in both the long- and short-term (that means that the *role* of forecasting in supporting decision making is crucial) and when forecast elaboration is not simply based on managers’ opinion (i.e. qualitative and/or quantitative forecasting techniques are adopted).

7. CONCLUSIONS

The main contribution of this paper is that it presents, compared to previous studies, a more comprehensive framework showing how the forecasting process can impact companies' performance. The results of this study offer new insights both for academics and practitioners. Firstly, the contribution of this research to the ongoing debate on the impact of forecasting on forecast accuracy is twofold:

- On the one hand, the present research does not support the opinion that adopting structured techniques always leads to improved forecast accuracy. This assumption cannot be considered generally valid. This is in line with those authors who maintain that the efficacy of forecasting techniques depends on the fit between the type of technique adopted and the context (Wright et al, 1996; Makridakis et al., 1998; Sanders and Manrodt, 2003).
- On the other, it demonstrates that, by leveraging on how the forecasting process is conducted (e.g. information collected or use of forecasting for decision-making), forecast accuracy could increase significantly. This emphasizes the attention that companies are paying towards a proper redesign of the forecasting process. Moreover this result confirms that part of the current literature highlighting the importance of organization and managerial issues in demand forecasting (Mentzer and Khan, 1997; Mentzer and Bienstock, 1998; Moon and Mentzer, 1998).

A further and innovative result of this research is that forecasting process variables have a *direct* impact on both cost and delivery performance. In particular, the use of forecasting techniques, the adoption of a forecast-based decision-making approach, and the use of several sources of information are both positively related with cost and delivery performance.

Thus, in designing a forecasting process, attention should not be paid only to accuracy but also to how forecasting could be used to improve cost or delivery performance (Winklhofer and Diamantopoulos, 2002; Småros, 2007). For example, as exemplified in the previous section, information that the forecast provides to users can be exploited in different ways and often helps functions to optimize their decisions, thus improving cost and delivery performance. Moreover, it should be noted that when a forecasting process is structured, it is usually recognized by all functions as a crucial process for achieving a competitive advantage and, as a consequence, functions are more motivated to align their decisions and plans with forecasts provided by their company, rather than elaborating their own forecasts. The consequent effect is that of reducing costs.

For all these reasons the design of the forecasting system should consider accuracy only as one objective among several: performance measures such as timeliness (Herbig et al., 1994), usability and credibility of the forecast (Mentzer and Cox, 1984) should be taken into account for an exhaustive evaluation.

From a managerial perspective, the results found can lead to interesting practical implications. Firstly, this research suggests to managers that when they redesign the company’s forecasting process, they should not focus only on single elements (e.g. forecasting techniques) to improve the process performance. All the different aspects that characterize it should be considered simultaneously, concerning the techniques to be adopted, procedures to be followed to collect data and disseminate forecast results, functions to be involved, etc. (Moon et al., 2003).

Moreover, the result that forecasting process variables have a direct impact on companies’ operational performance can lead to valuable and useful practical findings. In fact, it suggests to managers that the forecasting process needs to be designed coherently with the aim that should be achieved, which is not necessarily that of improving forecast accuracy. Just to give an example, ‘agile’ companies traditionally rely on reactivity to satisfy customers’ orders. Thus it could be argued that in this context forecasting management is not a priority. However, these companies could also obtain important advantages by redesigning their forecasting process. In fact, reactivity is also based on the ability to gather reliable and on-time information on market demand changes. A proper management of the forecasting process could guarantee this; e.g. analyzing data from customers on final market (VICS, 1998; ECR, 2001; 2002).

Finally, this study highlights several issues that could be considered in future research.

Though the results found prove that the adoption of structured forecasting techniques does not always improve forecast accuracy, this paper does not, however, specifically compare the efficacy of the different forecasting techniques in improving forecast accuracy. Future research could further contribute to the debate on the relationship between forecasting techniques and forecast error, by investigating the efficacy of specific techniques in different contexts. The need to adopt a contingency perspective in forecasting is claimed by several authors (Wright et al., 1996; Makridakis et al., 1998; Sanders and Manrodt, 2003). A contingency approach, besides suggesting under what conditions each forecasting technique is more beneficial, could also help companies foresee how their forecasting process should change in the future. The new millennium promises more demanding customers, greater competitive intensity, global networks with longer lead times, wider product variety and increased complexity in production technology. What will be the implications of these changes for the forecasting process and techniques?

Another opportunity for future research lies in the analysis of how forecasting variables can interact and influence forecast accuracy with a synergistic effect. In this paper, we have demonstrated that different forecasting variables impact on forecast accuracy, such as the use of several sources of information, and the adoption of a forecast-based decision making approach. However, how these variables interact to influence forecast accuracy is still not clear. As suggested by previous works, forecasting practices are deeply related to each other since companies tend to implement internally coherent processes (Kalchschmidt and Zotteri, 2007). The analysis of the synergistic effect of these variables could help to better understand the precise role of forecasting variables in improving forecast accuracy.

Finally, our future plans include an extension of this research, to further analyze the relationship between forecasting techniques and forecast error, and between forecast error and cost/delivery performance. As previously discussed, measuring forecast error in terms of MAPE involves the risk of overlooking the possibility that in some contexts an optimal forecast can deviate significantly from a least-mean-percentage-error prediction. One possibility would be to measure to what extent forecast error satisfies a company's objectives. Moreover, further research is needed to better comprehend the link between forecast error and cost/delivery. Survey data in this study do not support this relationship. This means that the simple assumption that: 'by increasing forecast accuracy delivery/cost performance improves' does not hold under all situations, and thus should be analyzed in more detail. In particular, the effect of forecast error on operational performance in make-to-stock vs make-to-order contexts is an interesting issue. For instance, it can be argued that in Make or Assembly to Order production systems, forecast accuracy is not essential in order to improve delivery performance, since other factors result as more critical, such as slack resources to guarantee the company's responsiveness to customers' requests. On the contrary, some authors (Wisner and Stanley, 1994) report that managers in JIT settings actually place more emphasis on accurate forecasting that those in non-JIT firms.

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