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The Impact of Forecasting on Manufacturing Performances

by

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The Impact of Forecasting on Manufacturing Performances

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Abstract

Several operations decisions are based on some kind of forecast of future demand. For this reason, manufacturing companies pay significant attention towards this process and research has devoted attention to this issue. This paper investigates the impact of how forecasting is conducted on accuracy and operational performances. Attention is here paid on three elements that characterize the forecasting process: whether structured techniques are adopted, whether detailed information is used, and the extent to which forecasting is used in decision making processes. Analyses are conducted by means of data provided by the fourth edition of the Global Manufacturing Research Group questionnaire. Data has been collect from 343 companies belonging to several manufacturing industries from 6 different countries. Empirical analysis shows that the relationship between how forecasting is conducted and operational performances is not fully explained only by taking into consideration forecast accuracy. Results show that companies adopting a structured forecasting process have positive impacts on operational performances (here manufacturing cost and delivery are considered) not only through improved accuracy. The paper highlights the importance of proper design of the forecasting process in manufacturing environments since it can help to better understand the forecasting problem (i.e. demand variability), may reduce bias and coordinates all forecast users.

Keywords: Demand forecasting, GMRG, Hierarchical regression, Accuracy

1. Introduction and Research Background

Demand forecasting has always been a relevant issue for manufacturing companies. Several decision making processes need accurate forecast in order to choose proper actions such as production planning, sales budgeting, new product launches, promotion planning, and so on. For this reason attention has always been paid in different industrial sectors to methods and tools that can improve accuracy in different industrial contexts. Companies have to properly define how to manage the forecasting process. This is not only a matter of what technique should be adopted, given a certain forecasting problem; it is also an issue in terms of information gathering processes and tools (i.e., what information should be collected), organization (i.e., who should be in charge of forecasting, and which roles should be designed), management of the process (i.e., the collaboration within the company between different organizational units, and outside the company with customers, suppliers and along the supply chain) and measurement of accuracy (i.e., use the proper metric and define proper incentive mechanisms).

Literature regarding the impact of forecasting on companies performances has devoted significant attention on accuracy and its role. The importance of forecast error on manufacturing systems has been understood since the earliest writings on production planning and control [1]. Inaccuracies in forecasting can mean excess inventories or lost sales and can lead to severe cost impacts on manufacturing systems ([2], [3], [4], [5]). So it is no surprise that several surveys show accuracy as the most important criterion in selecting a forecasting approach [6], [7]. Forecast inaccuracy causes major rescheduling and cost difficulties for manufacturing and it may impact on logistic performances such as delivery timeliness and quality [8]. For this reason some authors have even recommended to get rid of forecasts entirely [9].

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

Conflicting evidence is found when the relationship between the type of technique used and accuracy achieved is studied ([10], [11], [12]). A vast debate is ongoing regarding the efficacy of quantitative approaches (such as exponential smoothing or regression) and qualitative approaches (such as intentions, panel of experts, etc.). Sanders and Manrodt [13] provide a review of the contributions to this debate. Even if the discussion is not closed, what seems to be important is to use the right approach for the right problem: judgmental approaches seem to be preferable when demand is highly variable and affected by special events such as promotional activities, 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), when good quality data is available and when demand is rather stable [14], [15]. Integrating quantitative and judgmental approaches has also been suggested. Sanders and Ritzman [53] provide evidence of potential benefits of combining approaches.

Information sharing is also considered a relevant topic. It provides more knowledge regarding what future demand will occur and thus may be related to better accuracy [16], [17], [18], [19]. On the contrary, however, it is costly to gain lot of information and thus proper trade-off analysis has to be conducted [20] and in certain cases it may lead to misleading beliefs if it is not properly managed [21].

Evidence, in the end, has shown that the more companies tend to use structured approaches for forecasting demand based on specific procedures (i.e. they rely less on management opinion, collect systematic information and base their decisional processes on forecasts), the more their performances improve [22], [23]. Evidence has been provided that the use of structured forecasting process may have significant impacts of companies' performances not only in terms of better accuracy. The use of systematic data collection and management may be beneficial since it provides other processes with better information; the use of structured forecasting approaches may be helpful in defining proper objectives for sales people and production units; a proper evaluation of demand uncertainty may be helpful in anticipating hedging actions to reduce the impact of uncertainty on performance (i.e., better use of slacks, better aggregate planning of productions, etc.). Thus having a structured forecasting process may be helpful also despite its impact on forecasting accuracy [24], [25], [26]. Some authors provide evidence that, regardless of the specific technique used, when the forecasting process is not structured this may lead to worse performances [8], [12]. Literature suggests that good forecasts are not achieved only by the use of complex techniques [27], but also by a proper management of the process [26].

The forecasting process has thus changed its role over time: if at first attention was mainly given to the quality of forecast in terms of accuracy, now forecasting becomes an important process also to better manage product life cycles and customer relationship. New methods such as Collaborative Planning, Forecasting and Replenishment (CPFR) have shown that when structured processes are initially developed in order to improve accuracy, subsequently several indirect effects show up. Companies understand better their market and their customers, in terms of needs and preferences; companies use forecast proactively and not only as a simple goal that needs to be achieved, thus managing marketing and sales efforts more efficiently; companies share better information since data collection is done more accurately and with a clear definition of who is in charge of managing it.

This paper aims to study in deeper detail the relationship between how forecasting is conducted and companies performances. In particular, in the next section research objectives and hypotheses are defined and discussed; section 3 will then present the research methodology adopted and section 4 the empirical results. In the end section 5 will draw some conclusions and highlight future developments of this research issue.

2. Research Objectives and Hypothesis

The aim of this paper is to analyse the impact of using a structured forecasting process on companies' performances. Specifically, the goal of the paper is twofold:

1. first of all we aim to study the impact of how forecasting is conducted (i.e. the extent to which the process is structured) on forecasting performances (i.e. accuracy);
2. on a second hand, we aim to study the impact of forecast accuracy on operational performances, with specific attention to those performances that are typically influenced by demand variability.

In order to achieve these goals, we first describe the relevant variables here considered and then formulate specific hypotheses to be tested in the next part.

Different elements constitute and characterize the forecasting process and some authors have proposed different frameworks to analyse the process. Armstrong [27] considers four dimensions: forecasting methods (i.e., the kind of technique used, the number of techniques used, etc.), data available (i.e., central bank data is available), uncertainty (i.e., upper and lower bounds provided), costs and benefits (i.e., amount spent on forecasting). Fildes and Hastings [22] consider three variables: the forecaster and the decision maker (i.e., forecaster's training, forecast and decision making), information flows (i.e., information regarding environment) and technical characteristics of the forecast (i.e., accuracy and bias). Moon et al. [26] consider four dimensions: functional integration (i.e., degree of communication and coordination between forecasting and other functional areas), approach (i.e., the kind of technique used), systems (i.e., electronic links, information availability), performance measurement (i.e., measurement of accuracy). All these variables can be summarised in four main items (see table 1), three describing how the process is managed (i.e., techniques, information and role) and one related to the performances achieved (i.e., accuracy). Given the objectives of this work we consider three dimensions along which we analyse the forecasting process: techniques, information and role.

	Armstrong [27]	Fildes and Hastings [22]	Moon et al. [26]
Techniques	Forecasting methods	Forecaster and decision maker	Approach
Information	Data available	Information flows	Functional integration Systems
Role	-	Forecaster and decision maker	-
Accuracy	Cost and benefits Uncertainty	Technical characteristics of the forecast	Performance measurement

Table 1. Variables used in literature to describe the forecasting process

The relationship between the type of technique used and accuracy achieved is not straightforward (see section 1). This may be due to several reasons: first of all the forecasting problem changes in different contexts, specifically the use of a certain technique may be not enough to gain good performances if demand is highly variable or uncertain, while it may be good enough if demand is rather stable or predictable. On a second perspective, some techniques may be more efficient according to the nature of demand variability. For example, in the textile industry, qualitative approaches such as expert opinion may be very effective on fashion products for which quantitative techniques may be not adopted [18]; on the contrary, non-fashion products may be better forecasted by quantitative approaches that rely on available historical data. Even if the kind of forecasting approach used may be not related to accuracy, literature claims that using structured techniques may be helpful [26] since it reduces judgmental bias and the effect of irrelevant information [15]. For this reason we formulate the following hypothesis:

H1: The use of structured techniques is positively related to forecast accuracy.

Other authors have focused on the role of information on forecast accuracy. Several contributions show that additional information can enhance the performance of the planning process (see section 1). Collecting information from different sources may be beneficial since it can anticipate future customers' requests and may help in better understanding the value of each single piece of information [18]. Thus we formulate the following hypothesis:

H2: The use of several sources of information is positively related to forecast accuracy.

A key issue in understanding the impact of forecasting is also the role of forecasting itself. Several companies use forecasting for production planning, for sales budgeting, for purchasing plans and for planning long term investments [28], [29]. The more decision making is forecast-based the more accuracy becomes relevant; those companies that are not capable of gaining accurate forecast will pay less attention on forecasting accuracy and spend their efforts in coping with demand variability by other means (e.g., flexible manufacturing systems, inventories, etc.). For this reason we formulate the following hypothesis:

H3: The more decision making processes are based on forecasts the more forecast accuracy improves.

Forecast accuracy is not important per se but it is a fundamental issue since it may improve operational performances. Literature has provided evidence regarding this relationship, showing that accuracy improves the trade-off between inventory investments and service level [30] and it has significant cost impacts on manufacturing systems (see section 1). Companies pay attention to several performances, literature regarding the impact of forecast errors typically focuses on cost and delivery measures. Inventory cost is frequently considered ([31], [32], [33]) but some authors have also taken into account the impact on the overall manufacturing systems in terms of manufacturing costs ([2], [3], [4], [5]). Other authors have analyzed delivery performances showing that accurate forecast can make the product available when the customer orders thus reducing delivery and order fulfillment time and improving service level [30], [34]. Thus we formulate the following hypotheses:

H4a: Forecast accuracy is positively related to cost performances.
H4b. Forecast accuracy is positively related to delivery performances.

Some contributions claim that the relationship between accuracy and performances may not be so straightforward; sometimes companies pay significant attention to forecasting because this helps managerial processes indirectly [35]. Companies for example are able to better understand the effect of promotions on their demand by trying to better forecast demand affected by promotions [36]. By forecasting demand, companies may be able to better understand the market dynamics and improve their products or sales approaches. Companies may provide sales people with better information regarding future trends in the market so to improve their ability to rise margins and revenues, and to coordinate their actions.

Unfortunately literature does not provide evidence on this issue, so we formulate the following hypotheses:

H5a: The use of structured techniques, of several sources of information and of forecast-based decision making is positively related to cost and delivery performances.
H5b: The use of structured techniques, of several sources of information and of forecast-based decision making is positively related to cost and delivery performances.

Figure 1 synthesizes the research model we consider and describes the research hypotheses we want to test.

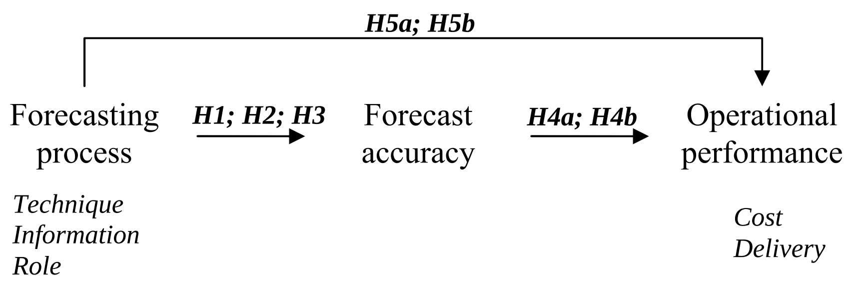

Figure 1. Research structure

3. Research Methodology

3.1 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 all over the world. Data is available from 343 companies in 6 different countries (Austria, Ghana, Hungary, Italy, Korea and Poland). Table 2 provides the sample sizes from each country. The sample is distributed among different companies' sizes (see table 3) and in different industrial sectors all belonging to the manufacturing and assembly industry. The sample is mainly constituted of medium size companies but also small and large ones are represented.

Country	Frequency	%
Austria	17	5.0
Ghana	63	18.4
Hungary	53	15.5
Italy	54	15.7
Korea	99	28.9
Poland	57	16.6

Table 2. The sample distribution over countries

Size	Frequency	%
Small (≤ 50 employees)	99	28.9
Medium (51 – 250 employees)	127	37.0
Large (> 250 employees)	112	32.7
N.A.	5	1.4

Table 2. The sample distribution according to company size

3.2 Measures

In order to analyse the available data, at first proper measures for each variable have to be defined. As previously stated, we analyse the extent to which the forecasting process is structured by means of three variables: extent of use of structured techniques, extent of use of structured information and forecast role in decision making.

In order to define the different constructs factor analysis and reliability verification are adopted. At first, those items that could be related to specific constructs are selected and their correlation is verified. Then factor analysis is applied by extracting all the eigenvalues that are above 1. When more than one factor is identified, Varimax rotation with Kaiser normalization is applied. Factors loads are verified in order to consider only items that have factor load above the minimum requirement of 0.40 [37], [38]. Reliability of the constructs is then checked by means of Cronbach's Alpha in order to verify that its value is above the minimum requirement of 0.6 [39].

To measure the extent to which structured techniques are used we have information regarding the extent to which each company uses quantitative time series models (i.e. exponential smoothing), quantitative causal models (i.e., regression) and qualitative models (i.e., market survey)*. These items are measured on a 7 point Likert scale ranging from 1 (Not at all) to 7 (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) and they are used to build a specific construct by means of factor analysis. A principal component analysis was conducted identifying that factor loads are all above 0.7 and that only one component is significant (total variance explained 63.1%). Cronbach's alpha is 0.70 confirming the reliability of the construct [40], [41]. Thus the construct *Structured Technique* is defined by averaging the three items.

Similarly, data on information used in the forecasting process is collected regarding the extent to which information on current economic conditions, sales plan, supplier information and market research was used. These items are measured on a 7 point Likert scale ranging from 1 (Not at all) to 7 (A great extent). The four 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. Cronbach's alpha is 0.68 confirming the reliability of the construct. Thus the construct *Structured Information* is defined by averaging the four items.

In the end, data concerning the role of forecasting in decision making is collected regarding the extent to which forecasting is used in sales and budget preparation, production planning, new product development, equipment planning. These items are measured on a 7 point Likert scale ranging from 1 (Not at all) to 7 (A great extent). The four 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 0.7. Cronbach's alpha is 0.73 confirming the reliability of the construct. Thus the construct *Structured Role* is defined by averaging the four items.

In order to measure forecast accuracy, we have information regarding the percentage error for an individual product for two months in the future and regarding the percentage error for the total sales of the plant for 24 months in the future. The use of the absolute percentage error is consistent with what previous surveys have employed ([42], [43], [44]). 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

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

variance explained 79.2%) and factor loads are 0.89. Cronbach's alpha is 0.74 confirming the reliability of the construct. Thus the construct *Forecast Error* is defined by averaging the two items.

In the end, operational performances are considered. We need variables that could take into account the overall effects of forecasting. Here we focus attention on the two main operational performances that are typically influenced by forecasting: costs and delivery. From the GMRG database we have information regarding 14 performances; items related to cost and delivery performances are considered, specifically direct manufacturing costs, total product costs, raw material costs, order fulfilment speed, delivery speed and delivery as promised. Companies were asked to provide an evaluation of their performances compared to their competitors on a 7 point Likert scale (1 is for "far worse than" and 7 for "far better than"). A principal component analysis has been conducted identifying two factors one related to cost performances (i.e., direct manufacturing costs, total product costs, raw material costs) and one regarding delivery (i.e., order fulfilment speed, delivery speed and delivery as promised). Factor loads are all above 0.8 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 two operational performance constructs here defined, we verify their relationship with two quantitative measures that related at least partially with these measures (see table 4 and 5). Cost performance is positively correlated with the percentage increase in labor productivity and delivery performance is negatively correlated with percentage late orders. These relationships even if they don't provide conclusive evidence on the quality of the constructs, at least claim that these measure are able to catch some of the variance in the sample. Table 6 synthesizes information regarding the constructs defined.

		Increase labor productivity
Cost	Pearson Correlation	0,145
	Sig. (2-tailed)	0,011
	N	309

Table 4. Correlation between cost and increase labour productivity

		% late orders
Delivery	Pearson Correlation	-0,271
	Sig. (2-tailed)	0,000
	N	247

Table 5. Correlation between delivery and percentage late orders

Construct	**Average**	**Cronbach's Alpha**	**Item**
Structured techniques	3.45	0.70	Quantitative time series models
			Quantitative causal models
			Qualitative models
Structured information	4.54	0.68	Current economic conditions
			Sales plan
			Supplier information
			Market research
Structured role	4.77	0.73	Sales and budget preparation
			Production planning
			New product
			Equipment 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 fulfilment speed
			Delivery speed
			Delivery as promised

Table 6. The defined constructs

4. Empirical Analysis

In order to analyse the first three hypotheses simple correlation between Forecast Error and the three process constructs is evaluated (see table 7).

As it can be noted, there are significant and negative correlations between forecast error and both structured information and structure role. This confirms previous literature results that the more information is provided to the forecasting process the more accurate is, regardless the way in which it is used and the context considered. Similarly those companies that base their decision making on demand forecasting are also those where forecast is more accurate. Thus we claim that hypotheses **H2** and **H3** are verified. On the contrary, the correlation between forecast error and the use of structured technique, even if it is negative as we may have anticipated, is not significant (Sig. > 0.05). Thus we cannot fully claim that a relationship exists between the two variables and reject hypothesis **H1**. This result is consistent with previous findings that show that this relationship is not always verified. This may be due to the fact that in different contexts a specific percentage error may have different impacts in terms of performances and may then be considered a satisfactory performance also according to the kind of variability the market faces. This claims that adopting structured techniques is not sufficient to have good performances, but other actions are needed.

		Structured Technique	Structured Information	Structured Role
Forecast error	Pearson correlation	-0.112	-0.169	-0.157
	Sig. (2 tailed)	0.066	0.005	0.010
	N	270	268	268

Table 7. Correlation between forecast error and process variables

To analyse hypotheses **H4a**, **H4b**, **H5a** and **H5b** hierarchical regression is adopted in order to verify first the relationship between forecast error and operational performances, and then the direct effect of the process variables. The hierarchical regressions are conducted according to the following procedure:

1. at first only control variables are considered in the model; here the size of the company is considered, as done in previous works (e.g., [45], [46], [47]). The impact of the industrial sector has also been considered, but it is here omitted for simplicity since it doesn't provide any significant result.
2. On a second step we introduce the forecast error.
3. In the end the three process variables are introduced.

At each step, in order to verify that the added variables provide significant contributions to the relationship, attention is paid to changes in the significance of the estimates and to the significance of the changes in the R square. Since some of the variables are also correlated, collinearity is checked by controlling the Variance Inflation Factor (VIF); in all the analyses collinearity does not harm any result. Two separate hierarchical regressions are conducted: one for cost and one for delivery as dependent variables. Table 8 provides details regarding the regression models on cost performances; table 9 provides comparison statistics of the different models on cost performances.

Model	Variable	Unstandardized Coefficients		Standardized Coefficients	Sig.	VIF
		B	Std. Error	Beta		
1	(Constant)	4,378	0,066		0,000	
	N. employees	0,000	0,000	0,156	0,014	1,000
2	(Constant)	4,575	0,087		0,000	
	N. employees	0,000	0,000	0,138	0,027	1,007
	Forecast Error	-1,092	0,319	-0,212	0,001	1,007
3	(Constant)	2,981	0,271		0,000	
	N. employees	0,000	0,000	0,083	0,155	1,040
	Forecast Error	-0,828	0,300	-0,160	0,006	1,029
	Technique	0,107	0,051	0,144	0,038	1,454
	Information	0,162	0,062	0,196	0,009	1,717
	Role	0,096	0,059	0,118	0,106	1,606

Table 8. Regression coefficients and variables' significance (cost as dependent variable)

Model	R Square	Adjusted R Square	R Square Change	Sig. F Change
1	0,024	0,020	0,024	0.014
2	0,069	0,061	0,044	0.001
3	0,207	0,191	0,139	0.000

Table 9. Comparison between the models considered (cost as dependent variable)

Model 1: the control variable is significant, even if explained variance is almost zero.

Model 2: when forecast error is introduced in the model, the variable is significant and the change in R square is significant too, even if still very low. This is consistent with previous contributions that claim that forecast accuracy has impacts on manufacturing performances. By improving accuracy, it is possible to better plan production capacity on both short and long term, it is possible to cope better with demand fluctuation and level production so to reduce the need of overtime workers or external capacity supply. Material flow can be better managed and beneficial agreements can be established with suppliers (e.g., better prices in exchange of more accurate anticipations on orders). In the end, accuracy can reduce inventory investment so reducing indirect cost that can impact on the total cost of production.

<u>Model 3</u>: when process variable are introduced we can notice that R square improves significantly and to a great extent (adjusted R square is almost 20%). We claim that this improvement is significant since we are considering an aggregate variable (i.e., cost) that will depend on several other actions that are not considered here (i.e., production planning, supply management, logistic management, etc.). While control variable is not significant anymore, forecast error is still a significant variable, but both technique and information are significant too. This claims that using structured techniques and information (i.e., adopt a more structured process) doesn't provide only better forecast, but it impacts directly the company's performances. This makes sense since using a structured approach lets understand better demand and markets so to identify specific patterns or buying behaviors. Adopting structured techniques can also reduce the possibility of judgmental bias and can help in providing to different functional units specific information to better understand demand patterns or characteristics. Collecting structured information may be beneficial since it can provide organizational units with better information to improve customer relationship or supplier management. At the same time, involving suppliers in the forecasting process can help in better understanding market dynamics or focus on specific material sources. This may help in reducing uncertainty for the company or define better future possible scenarios. From these considerations we accept hypotheses **H4a** and **H5a**.

A similar analysis is provided for delivery performances (see table 10 and 11).

<u>Model 1</u>: control variable is not significant and no relevant regression is found.

<u>Model 2</u>: quite interestingly forecast error is not significant in the relationship with delivery performance. This result is particularly interesting if we consider that companies should better manage their flows if proper forecast is provided and may reduce order fulfilment speed if the product is provided when needed. This result claims that this may not be the case probably because the different companies adopt different production systems. For example, companies where production is based on a Make to Stock logic may benefit from proper demand forecasting, but this may not be true for Make or Assembly to Order production systems, where good performances in demand forecasting may not be that beneficial and thus may not be of that interest. In this situation companies may gain more results by leveraging on flexibility given that certain knowledge on aggregate demand is provided.

<u>Model 3</u>: when process variables are considered, we can see that the R square improves significantly (adjusted R square is 14.8%) and technique and role become significant. The use

of a structured forecasting process, gives to the company the possibility of driving commercial choices. Sales people can influence (at least at some rate) customers' preferences and if their involvement in the definition of the forecast is significant (at least in the forecast interpretation) they can be easily be motivated to consider also the production perspective and contributing to delivery efficacy (i.e., influence customers to buy products that are already available or that can be easily manufactured and transported). This effect is true specifically when the forecasting process is considered in several decision making activities and it is not simply based on managers' opinion. This result is consistent with those authors that claim that forecasting should involve clearly different organizational units. From this consideration we reject hypothesis **H4b** but accept hypothesis **H5b**.

Model	Variable	Unstandardized Coefficients		Standardized Coefficients	Sig.	VIF
		B	Std. Error	Beta		
1	(Constant)	5,239	0,072		0,000	
	N. employees	0,000	0,000	0,014	0,847	1,000
2	(Constant)	5,213	0,093		0,000	
	N. employees	0,000	0,000	0,016	0,822	1,006
	Forecast Error	0,162	0,372	0,031	0,664	1,006
3	(Constant)	3,752	0,289		0,000	
	N. employees	0,000	0,000	-0,048	0,474	1,039
	Forecast Error	0,330	0,349	0,063	0,345	1,046
	Technique	0,187	0,056	0,272	0,001	1,526
	Information	0,031	0,067	0,040	0,645	1,768
	Role	0,136	0,064	0,177	0,035	1,639

Table 10. Regression coefficients and variables' significance (delivery as dependent variable)

Model	R Square	Adjusted R Square	R Square Change	Sig. F Change
1	0,000	-0,005	0,000	0,847
2	0,001	-0,009	0,001	0,664
3	0,169	0,148	0,168	0,000

Table 11. Comparison between the models considered (delivery as dependent variable)

5. Conclusions

This paper contributes to the understanding of the impact of forecast accuracy on operation performance. Results show that having a structured forecasting process may positively impact on forecasting performances. This emphasises the attention that companies are paying towards proper design of their forecasting process. It also contributes to that part of current literature that highlights the importance of organization and managerial issues in demand forecasting. The empirical analysis provides also evidence of the impact of forecast accuracy on companies' performance. Quite interestingly while the relationship with cost performances is significant this is not true for delivery performances. This means that the relationship between accuracy and operational performances is probably more complex and should be analysed in deeper detailed. Specifically, here we assumed a linear relationship between the two variables, which may not be the case.

An interesting result is that the direct relationship between how the process is conducted and operational performance seems to be stronger than the indirect relationship through accuracy. This result arises several considerations. First of all, the forecasting process needs to be designed coherently with the forecasting problem and by taking into consideration the different elements that characterize it (i.e., techniques, organization, procedures, information, etc. [26]). On a second hand, this result emphasises that performance improvements can be gained through an overall redesign of the process and not by acting on single elements such as techniques or information. In the end, the design of a forecasting system should take into account how it may at best serve its users. Attention should not be paid only to accuracy but also to the information that this forecast provides to users [35]. For this reason the design of the forecasting system should consider accuracy only as one objective among several: performances such as timeliness [48], usability and credibility of the forecast [49] should be taken into account for an exhaustive evaluation.

The work highlights several issues that should be considered in future researches. A first improvement of this work should be to expand the kind and number of variables used to analyse the forecasting process, such as organization that previous works highlight as significant (e.g., [50], [51], [52]). A second interesting improvement would be to study whether the kind of production system contributes to the understanding of the investigated relationship (e.g., is the relationship stronger in MTS environments compared to ATO ones?). Interesting topic is also the relationship between the variables that constitute the process. Previous works show that companies tend to implement forecasting practices coherently with their objectives [8]; however it is not clear to what extent this coherence influences forecast performances. In the end replication of this analysis on larger and different data sets would be important in order to verify the validity of results.

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