

STEFANIE PROTZNER

Mind the Gap between Demand and Supply

A behavioral perspective on demand forecasting



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Mind the gap tussen vraag en aanbod:
een gedragsmatig perspectief op vraagvoorspelling

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1 Introduction

1.1 The forecasting dilemma

“Prediction is very difficult. Especially if it is about the future.” – Niels Bohr

There is plenty of anecdotal evidence about the failure to forecast. Even experts can be mistaken in their predictions about the future, for example when Decca Records rejected the Beatles after an audition in 1962 arguing that *“guitar groups are on their way out”*. Similarly, Charles H. Duell, director of the U.S. Patent Office, advised that the office should be closed in 1899 as *“everything that can be invented has been invented.”* And Franz Beckenbauer, German football manager, predicted a bright future for the German national team in 1990 saying *“the German football team will be unbeatable in the future.”* Nowadays we know that none of these predictions was fairly accurate.

But why should we care about forecasts in the first place?

Forecasting is important because it aids planning and reduces uncertainty. In daily life, most people listen to the weather forecast to decide whether or not to pack an umbrella. Hence, forecasting guides our actions to prepare ourselves for expected future events that will occur with a certain probability. In organizations, forecasting plays a pivotal role in the Sales and Operations Planning (S&OP) process. Companies need to estimate how much of their products will be sold in the next one, two or three months in order to plan their production accordingly. However, demand and supply are more and more uncertain due to global competition, rapidly changing consumer preferences, long lead times and supply chain disruptions. Mismatches between supply and demand, so called supply chain glitches, have been shown to affect a company’s short- and long-term profitability (Hendricks & Singhal, 2005; Hendricks & Singhal, 2009). Sources of supply chain glitches can be internal or external and inaccurate forecasts are one of the primary reasons (Hendricks & Singhal, 2003). Hence, although demand forecasts are important, the perfect forecast is usually impossible because the demand is influenced by a variety of factors and the degree of uncertainty is large (Fisher & Raman, 1996).

1.2 Traditional forecasting research

The forecasting literature usually distinguishes between two types of forecasting. Quantitative (or statistical) forecasts rely on an analysis of numerical data, whereas qualitative (or judgmental) forecasts are based on subjective beliefs (Ord & Fildes, 2012). Extrapolation or causal models are examples of quantitative forecasting techniques. Qualitative techniques include unaided judgment or expert surveys. Traditionally, research on forecasting has sought to determine which (quantitative) forecasting technique leads to the most accurate forecasts (e.g. Makridakis & Hibon, 2000), whether judgmental, statistical or a combination of both approaches leads to better forecasting performance (Sanders, 1992; Webby & O'Connor, 1996), how different forecasts can be integrated (e.g. Armstrong, 2001; Clemen, 1989; Makridakis & Winkler, 1983; Winkler, 1971) and how demand forecasts are shared between different parties along the supply chain (e.g. Aviv, 2001; Mishra, Raghunathan, & Yue, 2009). While research on forecasting has primarily focused on improving statistical forecasting methodologies (Fildes, 2006), human judgment remains an indispensable decision aid in practice to facilitate forecast generation (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). Therefore, understanding human judgment in forecasting tasks is important to improve forecasting processes and ultimately performance. Forecasting research has only recently begun to acknowledge this *human factor* in what appeared to be a predominantly mathematical problem in the past.

1.3 Behavioral research on forecasting

This dissertation is part of a growing research field called behavioral operations management (BOM) in which human behavior and cognition are incorporated into analytical models of operations management (Gino & Pisano, 2008). The assumption of rationality has been an important principle for operations management theory for decades. The work of Simon (1956) and Tversky and Kahneman (1974) called this assumption into question arguing that humans have limited information processing capability and are prone to psychological biases that affect their decisions. Such irrational behavior, however, cannot be solved by providing sufficient (monetary) incentives as suggested by traditional economic and operations theory (Gino & Pisano, 2008). Whereas economists began to

incorporate deviations from rationality into their models earlier in order to explain and predict behavior, BOM has not emerged as a research field until just a few years ago. This development is important as operations management usually offers prescriptions to practitioners. However, as long as “these prescriptions rest on models with ungrounded behavioral assumptions, their usefulness in practice might be limited” (Gino & Pisano, 2008, p. 679).

Since its emergence as an interdisciplinary research field, BOM combines insights from various disciplines and includes new research methodologies, such as behavioral experiments, to address the gaps between normative prescriptions and actual behavior across a wide variety of operations management contexts (Bendoly, Donohue, & Schultz, 2006). In their seminal paper, Schweitzer and Cachon (2000), for example, conducted behavioral experiments to examine the behavior of decision-makers in the classic Newsvendor problem. They found that when people had to choose an order quantity, they systematically deviated from optimal quantities that would maximize their expected profits. They also found that these choices could not be explained by risk-aversion or risk-seeking preferences as suggested by Prospect Theory (Tversky & Kahneman, 1974), but by the “anchoring and insufficient adjustment process in which subjects anchor on mean demand and adjust insufficiently toward optimal order quantity” (Schweitzer & Cachon, 2000, p. 418). This pioneering research has influenced many other researchers to investigate human behavior in inventory decision-making (e.g. Bolton & Katok, 2008; Bostian, Holt, & Smith, 2008; Lau, Hasija, & Bearden, 2014; Rudi & Drake, 2014). In addition, BOM research has ventured into many other operations domains, including project management (e.g. Sting, Loch, & Stempfhuber, 2015), quality management (e.g. Das, Pagell, Behm, & Veltri, 2008), production and workflow (e.g. Siemsen, Roth, & Balasubramanian, 2008), queuing and scheduling (e.g. Powell & Schultz, 2004), and, most important for this dissertation, forecasting (e.g. Kremer, Moritz, & Siemsen, 2011; Kremer, Siemsen, & Thomas, 2012; Moritz, Siemsen, & Kremer, 2014).

The BOM research field has seen a spike in behavioral experiments as the preferred research methodology in its early days. The rationale for using behavioral experiments is the possibility to exert control over situational factors and to complement analytical models (Bendoly et al., 2006). However, researchers have already started to employ a

greater arsenal of methodologies to investigate human behavior in operations management. Examples include surveys (e.g. De Koster, Stam, & Balk, 2011), case studies (e.g. Bendoly & Cotteleer, 2008) and simulation (e.g. Oliva & Sterman, 2001). An overview of the disciplines and methodologies combined in BOM research is shown in Table 1.1.

Table 1.1: Typical disciplines, methodologies and themes in BOM research

	Cognitive psychology	Social psychology	Group dynamics	System dynamics
Typical unit of analysis	Individual	Individual	Individual and group	Group and organization
Main methods	Controlled experiment; Math modeling	Controlled experiment; Survey methods	Controlled experiment; Survey methods	Simulation; Controlled experiments
Key themes	Heuristics, biases	Motivation / goals, feedback	Groupthink, Abilene paradox	Stocks-and-flows, delays

(adapted from Bendoly, Croson, Goncalves, & Schultz, 2010)

The work by Kahneman and Tversky (1974) also stimulated extensive research on judgment in forecasting (Lawrence, Goodwin, O'Connor, & Önköl, 2006). For example, researchers have examined to what extent people use heuristics (such as availability, representativeness and anchoring-and adjustment heuristic) to make predictions (Harvey, 2007). However, the role of biases and how they affect forecast accuracy has largely been neglected (Lawrence et al., 2006). More recently, the literature has investigated underlying cognitive processes that may impact forecasting performance (Moritz et al., 2014). Central to most behavioral research on forecasting, though, is a focus on individual decision-makers performing a forecasting task (Lawrence et al., 2006). This is unfortunate as forecast decisions in many organizations are made by groups as a result of which biases other than cognitive limitations may impact forecasting performance. In fact, research on organizational forecasting indicates that departmental roles influence human behavior in forecasting processes (Oliva & Watson, 2009; Önköl, Lawrence, & Zeynep Sayim, 2011).

1.4 Dissertation overview

In this dissertation, I will consider behavioral factors in demand forecasting on both the individual as well as group level. As such, I will draw upon theories ranging from cognitive and social psychology as well as group dynamics to complement the traditional theories on judgmental forecasting. To account for these different units of analysis, this dissertation also employs different research methodologies that allow for either contextually rich data from a real-world setting (such as the case study in Chapter 2) or focused observations about cause-and-effect relationships in very controlled environments (such as the behavioral experiments in Chapters 3 to 5). All chapters are stand-alone articles that either have been submitted to academic journals, or are prepared for submission. Therefore, I will use ‘we’ instead of ‘I’ to refer to the work that I have done with my co-authors (Laurens Rook, Sebastian Guerrero and Steef van de Velde in Chapter 2; Clint Pennings, Laurens Rook, and Jan van Dalen in Chapters 3 and 4; Michael Becker-Peth and Enno Siemsen in Chapter 5).

In Chapter 2, we explore how forecast ownership affects forecasting behavior in a cross-functional forecasting process and how forecast combination can be used to address forecast biases. The functional specialization and differentiation inherent to most organizations usually shapes forecasting behavior in such a way that it benefits departmental goals and agendas. Companies often struggle with achieving cross-functional alignment in supply chain planning processes (Oliva & Watson, 2011) and incorporating the information of the demand and supply side in order to improve forecast accuracy. By means of an in-depth case study of a global beverage company, we were able to track two major change initiatives – the change in forecast ownership from the Marketing to the Supply Chain Department, and the introduction of a methodology that mechanically combined departmental forecasts into one composite forecast. This allowed us to identify and describe the potential benefits that these two factors may exert on the effectiveness of the forecasting process. Conceptually, this study combines insights from forecasting research with social dilemma research and agency theory. As such, it not only employs a relatively uncommon research methodology within the field of BOM, but it also uses theories to explain group dynamics within an operations management context, which so far has not been extensively studied in the BOM literature.

Chapters 3 and 4 were inspired by the findings from the case study on forecast ownership and forecast combination. While the strength of case studies is to build theory, the inability to control for many influencing factors is undoubtedly one of their limitations. As our case study showed, the social context and more specifically the social dilemma that surrounds the forecasting process may have a huge impact on people's behavior. In order to examine our theoretical propositions, we (artificially) designed the social context around the forecasting process in two behavioral experiments to investigate inter-individual differences in a collaborative forecasting task. Whereas we observed three departmental groups in the case study (Sales, Marketing and Supply Chain), we simplified the context to a dyadic situation (Sales and Operations) in the experiments.

In Chapter 3, we examine to what extent departmental affiliation within a company shapes forecast and negotiation behavior in forecast meetings. Using insights from social dilemma and negotiation research, we explored the related issue, if and to what extent the sometimes detrimental effect of departmental affiliation on forecast accuracy can be attenuated by a forecaster's individual disposition towards cooperation and conflict. Taking the motivational orientation of decision-makers into account, our social psychological approach extends the existing work that mainly revolves around cognitive biases and how they affect choices and decisions (Bendoly et al., 2010).

In Chapter 4, we extend the study detailed in Chapter 3 by examining to what extent a forecaster produces accurate forecasts and shares credible information depending on the type of incentive – that is, a departmental incentive to pursue functional goals or a collective incentive to pursue forecast accuracy. In addition, we argue that goal concerns may explain forecasting and negotiation behavior in the collaborative forecasting process. As such this study extends the scope of the research in BOM examining motivations and goal structures to define de-biasing strategies instead of identifying gaps between normative models and actual decision-making behavior in operations contexts.

In Chapter 5, we return to the individual decision-maker who makes forecasts based on time-series data using judgment. We explore under what conditions people detect actual trends and inadequately react to illusionary trends. More specifically, we alter the components of a time-series (change, noise and trend) to specify forecast patterns that people exhibit under different forecast environments. We argue that besides the previously

identified pattern of trend damping more patterns exist and thereby, we show that the perception of trends in time-series data is more complex than previously thought. Table 1.2 provides an overview of the research topics, chosen methodologies and unit of analyses in this dissertation.

Table 1.2: Research overview

	Chapter 2	Chapter 3	Chapter 4	Chapter 5
Unit of analysis	Groups	Dyad	Dyad	Individual
Method	Case study	Controlled experiment	Controlled experiment	Controlled experiment
Key theme	Forecast ownership	Social motivation	Goal concerns	Trend detection

Chapter 6 discusses the general findings of the studies described in the previous chapters. I will also relate the findings to the broader literature and highlight the main theoretical contributions of this dissertation. Finally, I will summarize the practical implications of this research for managers in forecasting processes.

2 Forecast ownership matters for supply chain planning: A case study in the beverage industry

In this study, we explore the effects of formal ownership and forecast combination as a means to improve forecast performance and cross-functional collaboration. Results from an in-depth case study show that changes in forecast ownership improved forecast accuracy at the expense of undermining the relationships between the Sales, Marketing and Supply Chain Departments. A mechanical weighting scheme combining departmental forecasts into one composite forecast reduced dysfunctional behavior and improved the effectiveness of the entire forecasting process. We also found that feelings of ownership aligned the interests of the stakeholders in the presence of diverging incentives and the absence of formal ownership. Taken together, this leads us to conclude that assigning forecast ownership to the department that assumedly has the highest vested interest in producing accurate forecasts may improve forecast accuracy in the short-term. However, it cannot eliminate the systematic forecast biases to over- or under-forecast that are inherent in functional differentiation. Any attempt to improve forecast accuracy needs to consider and solve the social dilemma that decision-makers in the forecasting process face.

2.1 Introduction

Accuracy in demand forecasts is of vital importance for organizations that face seasonal demand and usually have insufficient capacity to meet demand in high peak periods (Fair, 1989; Krane & Braun, 1991). Failing to accurately predict demand may lead to inadequate capacity, excess inventory, poor customer service levels, and an overall mismatch between supply and demand with potentially detrimental impact on a company's short- and long-term profitability (Hendricks & Singhal, 2009). At the same time, demand forecasting is, by nature, a complicated process – because it usually includes members from different departments such as Marketing, Sales, Production and Operations (Lawrence, O'Connor, & Edmundson, 2000). Given the dispersed knowledge that may exist throughout the organization, and the diverging interests and incentives that shape

organizational behavior, the task of arriving at a consensus forecast within a company is highly challenging.

Typically, forecasts generated by different departments are often based on different information, distinct forecasting methodologies – ranging from purely judgmental to statistical – and prepared on different levels of aggregation, for example on SKU (stock keeping unit), brand or packaging level. Successful forecasting requires coordination between the departments and integration of the individual forecasts into one composite forecast (Sanders & Ritzman, 2004). However, the functional specialization and differentiation usually shapes forecasting behavior in such way that it benefits departmental goals and agendas. Individuals often find themselves in a *social dilemma* in which they must choose between their short-term self-interest and a long-term collective interest (Van Lange, Joireman, Parks, & Van Dijk, 2013), a *mixed-motive* situation that is arguably more pronounced in inter-departmental settings. Research on affective forecasting – that is predictions about emotional reactions to future events (Wilson & Gilbert, 2005) – highlights how forecasters tend to favor their own opinion over those of others and place higher weights on their own forecasts than statistical forecasts (Yaniv, 2004b). Thus, companies often struggle with achieving cross-functional alignment in supply chain planning processes (Oliva & Watson, 2011) and incorporating the information of the demand and supply side in order to improve forecast accuracy.

One way to improve the coordination of the stakeholders in the process is to assign a formal forecast owner who is responsible and accountable for the forecasting process and its outcomes. Conventional wisdom would predict that the commitment to a forecast and a forecasting process varies as a function of whether someone is an owner or non-owner of the process. Vast amounts of research on agency theory are devoted to analyzing the problem of incongruent interests and goals between owners (principals) and non-owners (agents) (Eisenhardt, 1989; Jensen & Meckling, 1976). Applying insights from agency theory, we explore the effect of formal forecast ownership on forecasting behavior. Typical mechanisms, such as stock ownership, studied in agency theory do not apply to this supply chain planning context. We particularly examine whether, alternatively, a methodology to combine the departmental forecasts can align diverging interests and de-bias dysfunctional forecasting behavior in the presence of misaligned incentives.

In the following section, we review the relevant literature. In Section 3 and 4, we describe our methodology and research site respectively. Section 5 is a chronological display of events which sets the stage for our propositions related to the shifting responsibility over the planning process, the implementation of a new forecasting methodology, and the commitment of non-owners in mixed-motive situations. Section 6 presents our analysis. In the final section (Section 7), we discuss the implications of our findings for researchers and practitioners.

2.2 Theoretical background

Demand forecasting usually requires information from multiple sources; in fact forecast decisions in many organizations are made by groups (Lawrence, Goodwin, O'Connor, & Önköl, 2006). The multiplicity of data and sources creates two challenges. First, there are individual as well as political factors, that compromise the quality of forecasts as people knowingly or unknowingly bias their individual forecasts and hence the outcome of the collaborative forecasting process. Second, as the individually created forecasts are often based on very different information and derived using different forecasting methods (Clemen, 1989) there needs to be a method to reconcile those forecasts.

2.2.1 Forecast biases

Oliva and Watson (2009) studied a cross-functional supply chain planning process that was impacted by differences in goals and incentives among the functions participating in the planning process. The authors identified two potential sources of forecast biases – intentional and unintentional – that affect forecasting performance. Intentional biases were driven by incentive misalignment and differences in the disposition of power, whereas unintentional biases were driven by cognitive limitations. When different departments are evaluated based on different criteria and rewarded for different activities, forecasts might be biased in such a way to benefit one's own agenda. For example, an Operations Department that is usually concerned with low inventory levels and smooth production might set the forecast rather low to avoid excessive stock and costly production swings (Shapiro, 1977). A Marketing Department, on the other hand, is concerned with market

share and sales. It might therefore push to inflate the forecast to have sufficient products in stock. Önkal, Lawrence and Sayim (2011) have experimentally examined the effect that differential roles may have on forecasting behavior in organizational settings. To mitigate those functional biases Oliva and Watson (2011) suggest a supply chain planning process with an independent group as the process owner and constructive engagement to align incentives and reduce biased forecasting behavior and hence improve planning quality.

Just like intentional biases, unintentional biases may shape and hence affect predictions about the future. Research on affective forecasting has shown that people routinely overestimate the intensity and duration of their emotional reactions to future events when predicting such reactions (Wilson & Gilbert, 2005). That is, people tend to focus on the particular event and fail to consider other future events that may decrease the intensity or shorten the duration of the emotional reaction to that particular future event. Recently, Dane and George (2014) proposed that organizational factors, such as organizational prestige or the extent of team work, may also strengthen or weaken biases surrounding affective forecasts. Similarly, incentive systems within organizations may amplify these biases and lead people to focus on particular departmental goals and unintentionally make forecasts in line with these incentives.

In the operations management context, biases might affect behavior in a wide range of tasks that involve the acquisition, processing, and interpretation of information from different sources. Specifically, forecasting as one operations management setting can be affected by the anchoring and adjustment heuristic, the confirmation bias, and availability heuristic resulting in systematically inaccurate predictions (Gino & Pisano, 2008). For example, sales forecasts may be anchored on last year's sales or a statistically derived prediction and decision-makers usually do not adjust this initial number enough to account for other factors. The confirmation bias may lead decision-makers to selectively search for information that is consistent with their initial belief while they may discount information that proves otherwise. Thus, in order to achieve predictions that are as accurate as possible and that are not affected by either intentional or unintentional biases, a forecasting process should be designed such that the impact of those biases is mitigated.

2.2.2 Forecast combination – judgmental and statistical

One difficulty of supply chain planning processes is the variety of information and methodologies used to derive a composite forecast. Inputs from the Marketing function are usually based on judgmental forecasting methods, such as market surveys or even a gut feeling, whereas inputs from the Operations function are usually based on statistical techniques, such as regression models. Through the combination of both types of forecasts, companies can achieve significant improvements in their forecast accuracy (e.g. Clemen, 1989; Makridakis & Winkler, 1983).

A number of methodologies have been proposed to integrate different forecasts (Armstrong, 2001). The combining of forecasts from different sources can be done in group discussions or mechanically using either averages or weighting schemes. When decision-makers combine their opinions in group discussions in order to improve accuracy, several factors influence the integration of several opinions, such as the perceived accuracy of another source or the extent of agreement with one's own judgment (Yaniv, 2004a). When forecasts are mechanically combined, past research has shown that using equal weights produces accurate forecasts for many types of forecasting (Clemen, 1989). Moreover, a study by Winkler (1967) showed that using weights based on past forecast accuracies did not outperform using equal weights. On the other hand, there is some evidence that using previous performance to determine the weights can produce more accurate forecasts (e.g. Lobo, 1991; Shamseldin, O'Connor, & Liang, 1997). However, most of these studies are void of organizational contexts with diverging incentives that bias forecasting behavior.

Unlike previous studies that evaluated these methodologies based on forecast accuracy, Sanders and Ritzman (2004) propose human factors, such as perception of forecast credibility and forecast ownership; and organizational factors, such as the location of final forecast generation to evaluate how well each integration methodology performs beyond forecast accuracy. Although the authors do not explicitly define ownership, they do refer to the ability to influence the composite forecast. While there is hardly any research on ownership in the forecasting literature, vast research on agency theory analyses the problems of incongruent interests of principals and agents (Eisenhardt, 1989; Jensen & Meckling, 1976).

2.2.3 Ownership in agency theory

In agency theory, the relationship between shareholders (principals) and managers (agents) is defined as “a contract under which one or more persons (the principal(s)) engage another person (the agent) to perform some service on their behalf which involves delegating some decision making authority to the agent” (Jensen & Meckling, 1976, p. 5). The problem that arises from that relationship is a potential conflict of interests and goals of the principal and agent – hence the agent may not behave in line with the principal’s desires (Eisenhardt, 1989). To overcome this problem, agency theory is concerned with defining appropriate contracts and incentives, such as bonuses, profit sharing, or stock ownership options that align the interests of the principal and the agent (Ang, Cole, & Lin, 2000; Brown, Sturman, & Simmering, 2003; Nyberg, Fulmer, Gerhart, & Carpenter, 2010).

In supply chain planning processes, there are no shareholders and managers as defined in the principal agent relationship. However, of those stakeholders who are involved in the planning process, there is usually one who is assigned with a formal ownership of the process, asserts certain rights and responsibilities within the process, and is accountable for the outcome of the process. On the other hand, the non-owning stakeholders without explicit rights and accountability indirectly exert influence by providing information and making forecast decisions that serve as input to the composite forecast. Similar to the principal agent problem, the interests and goals of the different stakeholders in the process are not aligned. The fundamental difference though is that the design of contracts or introduction of bonuses and stock ownership options are no means to align the stakeholders in the process. This begs into question how forecast ownership affects forecasting behavior in general and how forecast combination can be used to align the interests of the Supply Chain, Marketing and Sales Departments in the presence of diverging incentives?

2.3 Methodology

This paper presents an exploratory case study with the aim of understanding how forecast ownership affects forecasting behavior. A case study is “an empirical research that primarily uses contextually rich data from bounded real-world settings to investigate a

focused phenomenon” (Barratt, Choi, & Li, 2011, p. 329). A single case study is the preferred research strategy when there is limited existing theory that describes the phenomenon, and variables – including the relationships between them – that are not yet very well defined (Meredith, 1998; Stuart, McCutcheon, Handfield, McLachlin, & Samson, 2002; Voss, Tsiriktsis, & Frohlich, 2002). In this research, we selected a case company in the beverage industry (see below). Our rationale for doing so was that the concept of forecast ownership is not very well developed in the literature – essentially, there is a lack of research investigating how to address forecasting biases of functional areas. Moreover, the single case also enabled us to study the surrounding context of the forecasting process in detail over a period of time and to reflect on the effects of two major change initiatives in retrospect (Barratt et al., 2011; Voss et al., 2002).

2.3.1 Research site

Our research site, BevCo (the company’s real name has been changed) is a global beverage company with €2.6 billion in sales and an operating income of €324 million in 2009. It has 84 plants and more than 37,000 employees worldwide. The company produces natural and flavored waters and is active in a very dynamic fast moving consumer goods (FMCG) industry determined by high seasonality and volatility. This is clearly reflected in BevCo’s product range including products with long as well as short product life cycles. BevCo produces natural carbonated and non-carbonated waters, which are functional products with long life cycles (Fisher, 1997). Within the flavored waters, a variety of flavors is available, such as orange, grapefruit, and apple, and consumers can choose from sugar-free and vitamin-enriched drinks. In addition to the regular flavors, the company also launches seasonal flavors that only have a product life cycle of six months. All products are available in various formats (i.e., 0.5, 1.0 and 1.5 liter bottles).

BevCo is represented worldwide by country business units (CBUs). For our case study, we focused on a CBU in Latin America where BevCo has been the market leader for years. This CBU belonged to the top three in terms of the growth of BevCo worldwide and was among the top 10 CBUs generating the highest sales. In 2009, the CBU had €250 million in sales with an operating income of €35 million. The business of this particular CBU was growing rapidly throughout the period of our study with an annual growth of

about 20 percent (taking the entire product range into account) and approximately 50 percent for the flavored waters.

Within its market, the high volatility and seasonality heavily influenced the CBU's operations. Consumer demand for new tastes and formats was constantly changing and was very unpredictable, especially for the more innovative products with short product life cycles. In 2009, the CBU had approximately 70 SKUs in total. Every year, 10 to 15 SKUs were added due to new product launches (for example, a new flavor) or changes in packaging (for example, change in label or format). BevCo had a seasonal business as consumption depended on the temperature, especially in Latin America. Sales during the summer season were – and still are – almost twice as high as during winter due to the extremely high temperatures that led to peak consumption, especially in densely populated metropolitan areas that accounted for more than 50 percent of the sales.

For the present research, the case of the Latin American CBU was particularly relevant because two events took place at the time of our study that directly impacted forecast accuracy. First, forecast ownership changed, which rendered the research site a revelatory case (Yin, 2009) to offer insights about a phenomenon which was previously inaccessible to a scientific inquiry. Second, a new forecasting methodology to combine departmental forecasts into one composite forecast was introduced. Therefore, this case also extends and generalizes the findings of a similar study by Oliva and Watson (2011) to another industry. Both initiatives – the change in forecast ownership and the introduction of the new forecasting methodology – helped improve forecast accuracy, but had different effects (which will be discussed in greater detail below).

2.3.2 Data collection

For the present research, we applied two types of triangulation, data triangulation and investigator triangulation (Denzin, 1989) as a strategy to improve the validity and reliability of our case study findings (Stuart et al., 2002). Data triangulation refers to the use of different data sources, while investigator triangulation refers to the use of different researchers to detect or minimize biases resulting from the researcher as a person (Flick, 2009). At the data collection stage, we used and combined various primary and secondary

sources of company information. This enabled us to obtain data on different levels while addressing the same problem.

Thus, we interviewed different stakeholders of the process – three demand planners who were responsible for the forecasting process at three different points in time: Demand planner 1 had been with BevCo for 1.5 years before assuming the position from June 2007 to April 2009. During this time, the ownership of the forecasting process changed from the Marketing Department to the Supply Chain Department. Interestingly, this demand planner moved into a Sales role afterwards and provided us with insights into both perspectives. Demand planner 2 had worked as a raw material and packaging procurement planner for two years before taking over the role as the demand planner from May 2009 to December 2010. During this time, the new forecasting methodology was implemented. Demand planner 3 had worked in Purchasing and Procurement for almost three years before becoming the demand planner from January 2011 to June 2012. During this time, the forecasting methodology continued to be used. We also interviewed the planning manager who was in charge of the overall planning process including production planning, forecasting, and material planning from December 2007 to May 2011, and who had also been with BevCo since 2002.

To establish reliability (Yin, 2009), we had an explicit interview protocol developed before conducting the interviews (see Appendix A for an example). The aim of the interviews was to document how the planning process at BevCo had evolved, to understand how the process was perceived by different stakeholders and what the reasons were for particular behaviors that affected the forecast and the process. The interviews lasted from 30 to 90 minutes. We assured interviewees that the results would stay anonymous in order to facilitate open communication. Our main informant was interviewed several times; he was the Demand Planner 2 who initiated and led the change in the forecasting methodology. All interviews were conducted in English, face to face or via telephone. The interviews were semi-structured and allowed interviewees to explore topics that they considered relevant. We used follow-up emails to clarify some answers. All interviews were recorded, transcribed for data analysis, and sent back to the interviewees for verification.

Likewise, we accessed various sources of company information to complement the interviews. We studied archival material, such as process descriptions, organization charts, company and industry reports, worksheets, and presentation slides. Interestingly, we were allowed to use the results of an unpublished in-company survey that was conducted at the beginning of 2010. This survey provided us with an insight into how the forecasting process was perceived by the stakeholders from the Supply Chain, Marketing and Sales Departments at that time. The survey revealed how people judged the collaboration among the departments and how motivated they were to change to a new process. This enabled us to collect data from a wider sample of respondents that we did not have direct access to (Voss et al., 2002).

Importantly, we were also allowed access to the original forecast bias and accuracy data for the entire CBU for the eight most important brands for the period between January 2007 and August 2012. For the time period following the implementation of the new forecasting methodology (May to November 2010), we received more detailed data about the forecast, actual sales levels, forecast bias and accuracy for each of the three departments (Sales, Marketing, and Supply Chain) as well as the combined forecast for the 10 most important brands and all bottled products combined. This enabled us to conduct supplementary quantitative analyses examining the impact of the change in ownership and new forecasting methodology on the forecasting bias and forecast accuracy of each department and the CBU in total. As such, the quantitative data represented a different source of information to corroborate the findings from the interviews.

2.3.3 Data analysis

An inductive approach was followed for coding and analysis (Miles & Huberman, 1994). The coding technique we used is described in Strauss and Corbin (1990) and has been used in operations management research before (e.g. Barratt & Barratt, 2011; Karlsson, Nellore, & Soderquist, 1998; Wu & Pagell, 2011). Generally, collected data is written up, reviewed, and labels are generated for segments of text which are further reviewed and refined into more abstract categories. We started the coding process by reading through all of the material, identifying fragments of text that provided insights into ownership, the perception of the cross-functional interface and forecasting process, and the

behavior of involved stakeholders. This served as a first basis for developing a coding protocol. The categories that emerged revolved around themes that were explicitly mentioned by interviewees and survey respondents. After multiple iterations, some categories with substantial thematic overlap were refined into 23 thematic attributes. Appendix B features the labels, our operational definition and a sample text from our data for some of the key themes.

Using the qualitative data analysis software package NVivo 9.0, we coded the entire text material based on the coding protocol. Two researchers independently coded the data in order to minimize researcher bias during the analysis stage, another use of triangulation to improve the quality of our research. We relied on Cohen's kappa (Cohen, 1960) to assess inter-rater reliability. Contrary to other reliability measures, this statistic corrects for chance agreement and does not inflate the reliability score; kappa ranges from 1 to -1, with 1 indicating perfect agreement and 0 indicating chance agreement. We obtained an inter-rater reliability of 0.74, which is good (Cicchetti, 1994), especially in light of the observation made by Boyer and Verma (2000) that an initial standard of 0.60 is an acceptable level of inter-rater agreement in the operations strategy literature given the lack of established standards in this field.

2.4 Case Context

As a beverage company, BevCo operated in the fast moving consumer goods industry. The Latin American CBU under study not only faced the challenges typical for FMCG companies, but also dealt with dynamics that were specific to the Latin American market. Most notably, the high volatility and seasonality of the demand and supply side determined the CBU's operations and need for accurate demand forecasts.

2.4.1 Demand dynamics

As typical of the FMCG industry, competition was severe due to the large number of national and international competitors that were established in the Latin American market at the time, including private labels that were entering the market with the intention to steal market share by offering lower prices. At the same time, several market trends emerged that the CBU had to satisfy to stay competitive. Specifically, an increasing

awareness of health issues and changing lifestyles impacted the company's product range. That is, flavored waters had been positioned as healthier alternatives to soft drinks and hence the CBU frequently introduced new products to keep up with the changing taste of consumers. Similarly, the labeling and packaging greatly contributed to a consumer's decision to purchase a product. The CBU, therefore, needed to invest in innovations surrounding the labels and bottles.

Another factor contributing to high volatility was the importance of promotions. Capturing and estimating the impact of promotions on the CBU's sales, however, was a challenging task due to this very complex business environment, in which several factors affected consumer demand. In any case, over-forecasting demand could lead to an oversupply of products and under-forecasting could lead to shortages, both of which were unfavorable situations producing either obsolescence or stock-out costs.

Besides general market trends, seasonality heavily impacted product demand and influenced the CBU's entire planning process. High temperatures, especially during the summer season, could rapidly increase consumption. Furthermore, some of the new products were introduced only as a seasonal flavor during certain months of the year. Planning, purchasing of components (for example, fruit juice) and production were usually finished well in advance. Again, inaccurate forecasts could lead to an over- or undersupply situation.

Finally, demand for BevCo's products in this CBU was also affected by the governmental control over price increments, which was a specific characteristic of Latin America. As the prices for the raw material moved together with oil prices, this external control affected the company's profits.

2.4.2 Supply dynamics

On the supply side, the seasonality impacted the CBU's production. Production was handled by four factories in the country owned by the CBU and some third-party manufacturers for the packaging component. BevCo could not produce all of its demand during the peak season, because capacity constraints made it difficult to react flexibly to seasonal demand patterns. At the same time, most of the products were perishable and shelf life was part of BevCo's service contract with retailers. For example, for still waters,

the shelf life was usually 12 months, whereas for flavored waters, it was six months. Hence, fluctuating demand could not easily be satisfied by either increasing production capacity or plenty of safety stock as products could not be put in stock for a long period of time.

The raw materials were sourced from mainly Latin America and a few Overseas suppliers. An increase in the price of raw materials, such as PET for producing bottles, put a lot of pressure on BevCo's total cost price. The success of the CBU also depended to a large extent on how well it utilized its plants and how well it forecasted resource requirements. As it was very expensive to invest in new manufacturing facilities, there was a large amount of pressure on the existing capacity utilization. Moreover, it was critical to accurately forecast not only volumes but also the specific mix of SKUs (for instance, the different flavors), because the deals with the component suppliers were closed once every year. In other words, if the flavor forecast was inaccurate, BevCo ran the risk of having too little fruit juice for production, risking an undersupply situation.

Finally, distribution contributed to the high volatility. The CBU primarily sold its products through distributors (50 percent of sales) and retailers (20 percent of sales). The remaining 30 percent of sales targeted small neighborhood outlets that are very typical in Latin American countries. They amounted to up to 25,000 points of sale throughout the whole country. This channel required a large sales force and a complex logistics network to serve those businesses, but it was also the most profitable as there were no further intermediaries. However, with sales going through distributors, lead times and order variation were increased while total chain stock visibility was reduced. That made planning and fulfilling consumer demand very difficult.

In sum, given the high volatility and seasonality of BevCo's business, accurate forecasts were of vital importance to fulfill demand and keeping costs low. Too high or too low a demand forecast could lead to over- or under-supply, respectively. The CBU struggled with forecast inaccuracies which had severe effects on its operations. In order to understand the forecasting behavior of the different stakeholders in the forecasting process that led to over- and under-forecast situations, it is important to take the organizational context into account.

2.4.3 Organizational context

BevCo's Supply Chain, Marketing and Sales Departments differed considerably with regard to their responsibilities, objectives, and orientation. The Supply Chain Department managed the planning of demand, raw materials and production, and was responsible for transport and distribution. The Marketing Department was responsible for generating demand in the market, hence served as the direct link to the consumers through advertising and promotions. Marketing also defined pricing strategies and decided which products to launch or discontinue. The Sales Department served to persuade customers, for example, retailers to buy BevCo's products and fulfill customer needs, and was split into Sales Planning and Sales Execution.

These different tasks and responsibilities influenced the departments' priorities, planning horizons and incentives and also determined each department's attitude towards forecasting in general and its own forecasting behavior in particular. A summary is provided in Table 2.1. As the Supply Chain Department was partly compensated based on forecast performance, forecast accuracy was its most important KPI (key performance indicator). It aimed for accurate forecasts in order to lower stock levels and stabilize production knowing the impact that forecast accuracy had on service levels, inventory levels and write-offs. The Marketing Department was compensated based on brand yearly sales, brand market share and profitability, and brand operating contribution. Hence, Marketing was interested in bringing products to the market and ensuring high product availability. Enthusiastic sales projections and inflated demand forecast were Marketing's means of ensuring high inventory levels to avoid stock-outs, while predicting high demand would also justify its investments in promotional activities. For the Sales Department part of the variable salary depended on the achievement of a sales target, which was set with the forecast as an anchor. This led Sales to deflate the forecast in order to receive a less challenging sales target.

Table 2.1: Functional comparison

	Supply Chain	Marketing	Sales
Priorities	Low stock levels Stable production SKU level	Incentivize consumption (end consumers)	Fulfill sales volume objective (customers) Brand level
Horizon	Medium to long- term	Long-term	Short-term
Incentive	Forecast accuracy	Brand performance	Sales target
Bias	Conservative	Positive	Negative
Forecast creation	Historic sales data & regression models	Judgmental	Judgmental & statistical
Tools	Excel Forecasting software	Powerpoint	Excel

Consequently, the functional differentiation created natural tensions between the three departments, even in the pursuit of a collaborative forecasting process. The need for accurate forecasts, combined with the incentive landscape, created a *mixed motive situation* in which the aim of accurate forecasts was at odds with the aim of achieving personal (departmental) goals and incentives. This did not only pose a great challenge at aligning Supply Chain, Marketing and Sales, but also led to conflicts among the three departments. The emphasis on functional objectives represents a silo-oriented approach to managing the supply chain, which may subsequently be rooted in the incentive landscape of the organization. Similarly, an individual's problem solving approach may contribute to a narrow or broad focus and hence to the decisions that are primarily concerned with satisfying individual or overall objectives respectively (Cantor & Macdonald, 2009). In the

CBU's situation, the three different departments locally optimized their individual incentives while underestimating the impact that their forecasting behavior would have on the other parties.

2.5 The Planning Process

As described above, the planning process and an accurate demand forecast were of vital importance for the company due to the high volatility and seasonality of demand and a huge share of sales going through distributors. Demand seasonality posed a major challenge because the company did not have sufficient capacity to meet demand during the high season and had to anticipate stocks and plan capacity early to satisfy demand when it peaked. At the same time, perishable products became obsolete and the longer they were kept in stock, the shorter their shelf life that could be offered to customers. The use of distributors increased the lead times and order variation, which tended to increase when moving up the supply chain, a phenomenon known as the bullwhip effect (Lee, Padmanabhan, & Whang, 2004). It also decreased the stock visibility throughout the entire supply chain. The planning process at BevCo changed twice within a two year period to address the problems of inaccurate forecasts and lack of cross-functional collaboration. Initially the ownership of the forecasting process changed and later a new forecasting methodology was introduced. Both initiatives had very differential effects on the forecasting behavior and process, as will be discussed in the following sections.

2.5.1 The early forecasting process (2007 – 2009)

In the beginning, the Marketing Department created a monthly forecast based on their knowledge of the market. That forecast was communicated to the Supply Chain Planning Department which then created the production and procurement plans based on that forecast. No further adjustment of the forecast was made. Given Marketing's objectives and their sales projections, the forecast was usually higher than actual demand and led to forecast accuracies that sometimes fell to below 70 percent. Because of this low accuracy, BevCo had very high inventory levels, while at the same time service levels were well below the target. This resulted in high obsolescence costs, as the products had to

be written off when they were too close to the expiry date and could no longer be sold to customers.

In April 2008, the general manager assigned the responsibility of the forecast to Supply Chain. The goal of this initiative was to achieve better forecast accuracy leading to higher service levels and lower inventory levels. The forecasting process followed a monthly planning cycle: each week certain actions were required or meetings took place. In Week 1, Supply Chain created an initial forecast based on the information it had received from Marketing and Sales. In Week 2, the Marketing and Sales Departments created their demand forecasts separately in preparation for the forecast review meeting in Week 3. This forecast review meeting was attended by the Marketing and Supply Chain Planning Departments (as before), but now also the Sales Planning Department took part in the meeting. During that meeting, discrepancies between the three separate forecasts from Supply Chain, Marketing and Sales were discussed in order to decide on one consensus forecast, and thereby reducing the impact of potentially too high or low forecasts from the Marketing and Sales Departments, respectively.

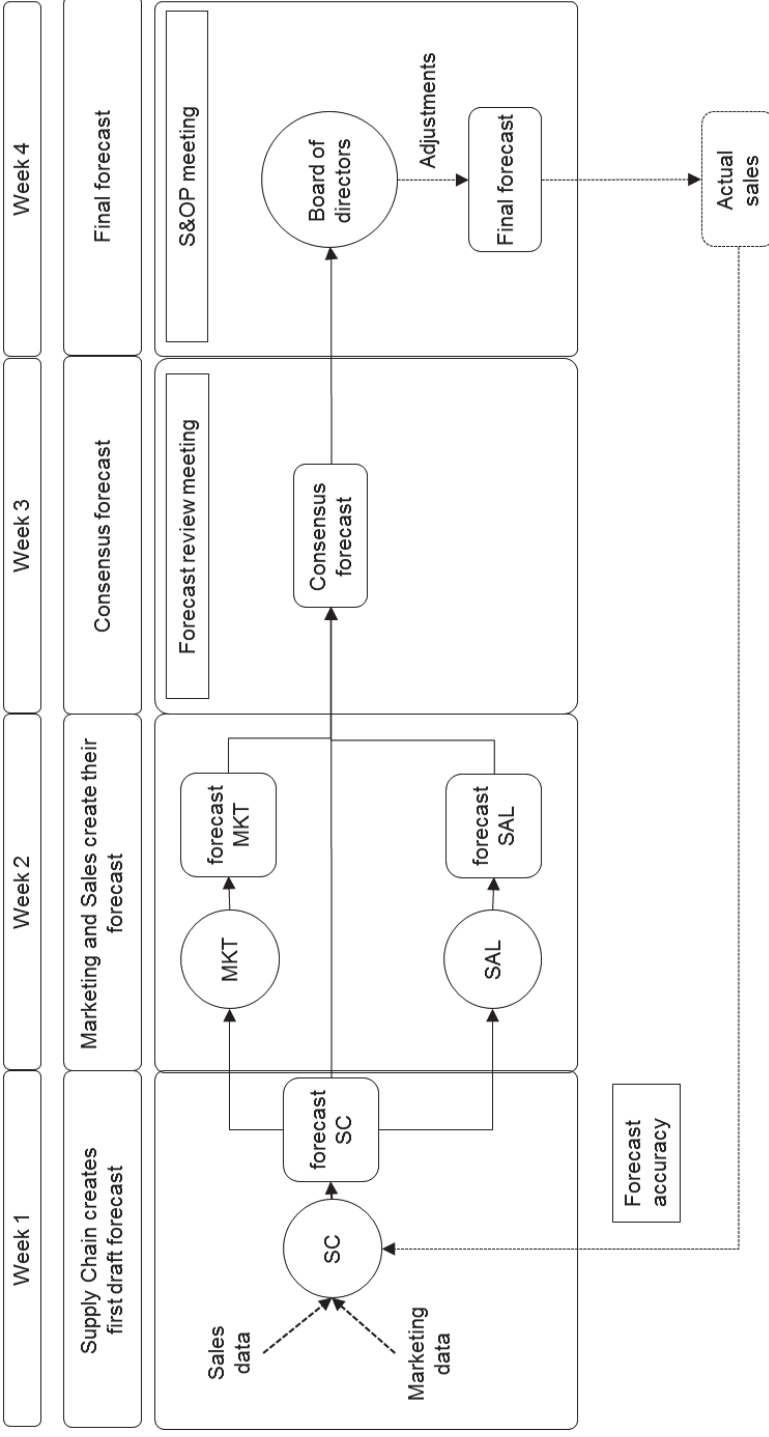
This meeting sometimes lasted an entire day and involved serious negotiations to reach a consensus forecast. The outcome of the discussion was heavily influenced by personal interests and the relative power of the attendees (in terms of persuasive power and seniority). For example, if the Marketing Department sent a junior brand manager to the forecast review meeting, it was more difficult for this manager to convince a more senior Sales manager that the consensus forecast should be higher. Participants in the meeting also changed from one month to the next due to internal company dynamics (for example, job rotations). The focus of this forecast review meeting was on the short-term, reviewing the forecast for the next month and sometimes the forecasts for the coming two or three months in order to first solve the pressing operational issues.

The consensus forecast was taken as an input for the Sales and Operations Planning (S&OP) meeting that took place in Week 4. In this S&OP meeting, the board of directors decided on the final forecast. In most cases, the directors changed the consensus forecast. However, at that time, the focus of the S&OP meeting was very short-term oriented addressing mainly capacity and supply issues. The S&OP meeting lacked senior involvement as not all directors were committed to participate in that meeting. The main

participants were the Supply Chain Planning manager, the Purchasing director and Production Planning manager, whereas there was very low attendance from the Sales or Marketing directors. Figure 2.1 provides an overview of the forecasting process at this early stage.

The forecast review meetings became ineffective due to the constant tension and conflict between all three parties trying to resolve the differences between the forecasts that were biased in opposite directions (with Marketing over-forecasting and Sales under-forecasting). This was the state of affairs when a demand planner took over the position in 2009. In the next section, we will describe how the new demand planner dealt with this problematic situation.

Figure 2.1: The early forecasting process

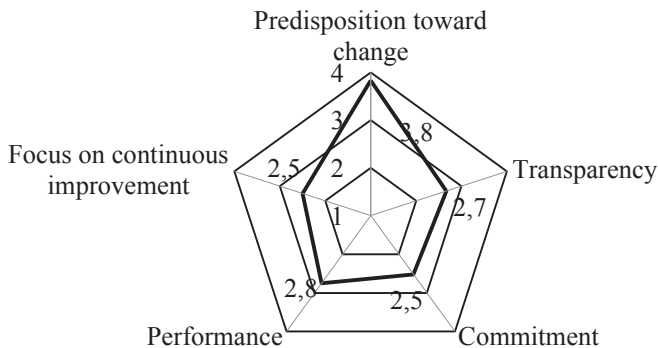


2.5.2 Transition to a new forecasting methodology

The demand planner who took over this position in May 2009 initiated a new forecasting methodology in April 2010 to formalize the forecasting process and address the forecast biases and improve forecast accuracy. The new demand planner first received senior support from the planning manager who was in charge of the overall planning process. However, as the buy-in of all functional groups was a necessary condition for the forecasting process to work, a top-down change would not have been successful. For this very reason, a survey was carried out with relevant stakeholders to, first of all, understand the different perspectives and how the current process was perceived, and to raise awareness of the need for a change.

In this survey, respondents were asked to indicate how satisfied they were with the current forecasting process. The survey addressed five themes: transparency of the process, performance of the process, commitment to the process, others' commitment to the process, and orientation towards continuous improvement. The survey revealed that the satisfaction with the existing process was very low whereas the willingness to change the process was very high as can be seen in Figure 2.2.

Figure 2.2: Radar chart of stakeholder survey results



The survey also included open-ended questions where respondents could give their general opinion about the process. An example of a Marketing manager was as follows:

“There is no standard template to create the forecast and to feed the inputs into the process. There is no knowledge about the methods used by the other departments to bring the number to the meeting. We fight to reach the number!”

Similarly, a Sales manager noted:

“We are not very quick to reach consensus. We fight a lot. It’s obvious that our positions are very biased in opposite directions because of the different interests. In the end, it’s a very subjective way of arriving at the forecast number. We lack some sort of standardization.”

The new forecasting methodology would need to address the concerns raised in the survey. Thus, the demand planner proceeded with the implementation of a new mechanical weighting scheme to create a more objective way of reaching the consensus forecasts and thereby reducing the propensity for particular forecast biases and the conflict around each department’s forecasting behavior.

2.5.3 The new forecasting methodology

In the new process, information sharing became more structured. Marketing, Sales, and Supply Chain had to write their individual forecasts in a shared database in Week 1. No-one had access to the other’s inputs before entering the forecast to avoid manipulating and biasing the forecast on purpose. An interesting feature of the new forecasting methodology was that the assumptions upon which the forecasts were based also had to be shared in the database. These were, for example, promotion plans, new product launches, anticipated special events in the future or stock levels of distributors. This was intended to increase the transparency of the information needed to make an accurate forecast.

In Week 2, the departmental forecasts were combined into one forecast using a spread sheet as a tool. The individual forecasts of the three departments were weighted according to their past average accuracy during the previous six months. This was the most prominent difference in the new forecasting process: the structured method to objectively determine the combined forecast instead of negotiating the final figure. The more accurate a departmental forecast had been in the past, the larger the weight that this particular

department would have in the forecast for the following month. While Supply Chain and Marketing were forecasting on SKU level, Sales forecasted on brand level, which had to be taken into account when calculating the final forecast on SKU level. Table 2.2 provides an example of how the separate forecasts were combined into the final forecast.

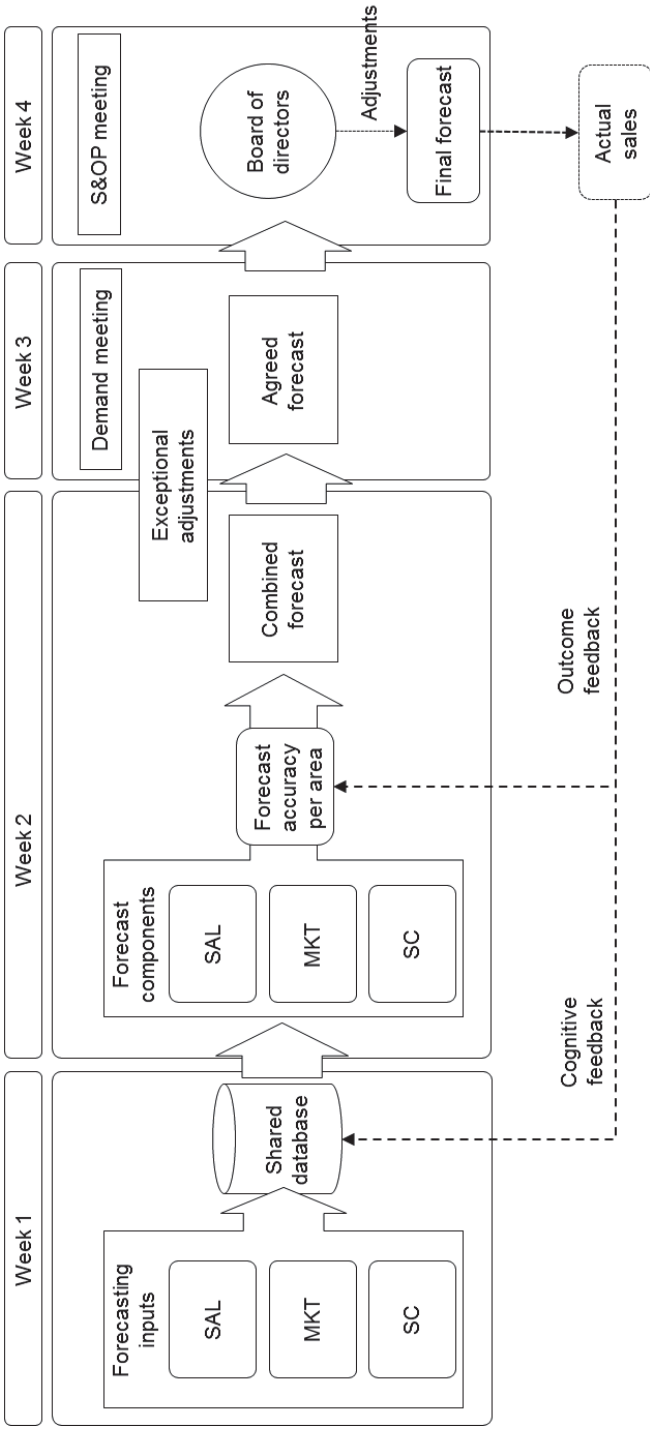
Table 2.2: Methodology to combine departmental forecasts

Brand	Average forecast accuracy			Weighting			Forecast source			
	<i>SC</i>	<i>MKT</i>	<i>SAL</i>	<i>SC</i>	<i>MKT</i>	<i>SAL</i>	<i>SC</i>	<i>MKT</i>	<i>SAL</i>	<i>Comb</i>
A	98%	96%	97%	36%	29%	35%	20,000	20,500	20,300	20,248
B	94%	94%	93%	35%	36%	29%	15,500	14,355	15,000	14,947

The results of this forecast combination were discussed in the forecast review meeting in Week 3 before they were communicated again as input for the S&OP meeting that took place in the Week 4 and was intended for the same participants as before. Figure 2.3 provides an overview of the new forecasting process.

With the new methodology to combine the departmental forecasts, the forecast review meetings started to change. First of all, the spread sheet tool provided the discrepancy between the highest and lowest of the three departmental forecasts. Only if this discrepancy was too large, the forecasts and their underlying assumptions were discussed, otherwise the objectively combined forecast was automatically accepted. This meant that there was more time available to also discuss more medium- and long-term strategic issues, as most of the serious discussions around the forecast were eliminated by this new approach. Secondly, the forecast performance of each department as well as overall (company) forecast performance of the previous months were shown and discussed during the meetings. This did not only facilitate learning, but it also increased transparency as well as accountability. Hence, the new forecasting methodology to objectively combine departmental forecasts into one consensus forecast based on past forecast accuracy solved the mixed-motive situation in which the aim of accurate forecasts was at odds with individual (departmental) goals.

Figure 2.3: The new forecasting process



2.6 Case Study Findings

In this section, we present our findings that complement the descriptive documentation of the planning process in the previous section.

2.6.1 The effect of formal forecast ownership

The first step in improving forecast accuracy was to assign the ownership of the forecasting process to the Supply Chain Department. By forecast ownership, we refer to a formal claim of ownership of the forecasting process. As such, the construct of forecast ownership can be distinguished from other types of formal ownership systems that provide equity possession to employees, such as the employee stock ownership plan (Toscano, 1983). Forecast ownership further refers to the planning and control over the forecasting process and its outcomes. A forecast owner is responsible for managing the process and synthesizing data (Oliva & Watson, 2009), but also for disseminating information to stakeholders of the process, and monitoring the performance of the process and adjusting it, if necessary. The owner thus bears the ultimate responsibility of the forecast. The location of forecast ownership varies in organizations as owners may be the Logistics, Sales, Marketing, Procurement or Production Department (Adebanjo & Mann, 2000). Also, cross-functional ownership has been discussed in the literature (Davis & Mentzer, 2007), but it merely refers to the development of a consensus forecast – that is to say, coming to an agreement among different stakeholders who can then be held accountable for this agreement.

The change in formal forecast ownership from the Marketing to Supply Chain Department at BevCo had two major consequences. First, the forecast performance improved dramatically. Before the change in ownership, average forecast accuracy ($1 - \text{ABS}[\text{sales}-\text{forecast}]/\text{forecast}$) from January 2007 until March 2008 was 81 percent. After the change in ownership, forecast accuracy increased to on average 88 percent, whereas forecast bias ($\text{sales}/\text{forecast}$) decreased from on average 7 percent to 2 percent. However, there was also a downside to the change in forecast ownership. While forecast performance improved due to the leading role of Supply Chain, the *conflict* between the three departments increased, especially between the Sales and Marketing Departments. The consensus forecast was often mistrusted and second-guessed when the plan was

communicated in other functional meetings. Tension could also be observed in the commitment of participants who failed to provide input to the forecast review meeting on time. A Supply Chain manager described the resulting conflict as follows:

“We became more like the enemy rather than a partner for Sales and especially for Marketing, because we would be challenging the forecast all the time and we would arrive to a forecast all the time that they didn’t feel was their own forecast. So, we lost their commitment in the process. They would not feel that we were partners. They would feel more like we were enemies.”

This lack of alignment and coordination started to jeopardize the entire planning process. That is, the change in ownership structure for the sake of accuracy improved performance, but had a detrimental effect on the relationships and commitment to the process. This leads to our first proposition regarding the effect of forecast ownership on forecasting behavior:

Proposition I. *Shifting forecast ownership from one department to another can improve forecast accuracy. This effect does not occur through a change in actual forecasting behavior, but through the ultimate decision-making authority of the owner. Forecast accuracy under such circumstances improves at the expense of losing commitment from the non-owner(s).*

2.6.2 The effect of a new forecasting methodology

The new forecasting methodology that mechanically combined the departmental forecasts into one composite forecast according to a weighting scheme based on past accuracies was key to aligning the diverging interests and goals of the stakeholders in the process. When BevCo started adopting this new methodology, the three departments needed to jointly get used to the new process, which caused an initial drop in forecast accuracy in April 2010. Afterwards, however, the forecasting performance continued to improve despite an increase in SKUs and the growing complexity of the business and market situation. Figures 2.4 and 2.5 show a steady decrease in overall forecast bias and increase in forecast accuracy, respectively. Interestingly, the range of the forecast also became narrower, hence the variability and predictability of the forecast improved

substantially, which made the overall forecasting process and entire supply chain more stable and robust.

The methodology to combine the three departmental forecasts eliminated the forecast bias that was generally observed in the company – that is, Marketing’s tendency to over-forecast and Sales’ tendency to under-forecast. Figures 2.6 and 2.7 compare the forecast accuracy and forecast bias per functional area with the combined forecast for all bottled drinks across all brands after the implementation of the new forecasting methodology. As can be seen, forecast accuracy increased and forecast bias decreased. The combined forecast did not necessarily outperform each individual forecasts, but represented an objectively calculated compromise.

Figure 2.4: Forecast bias

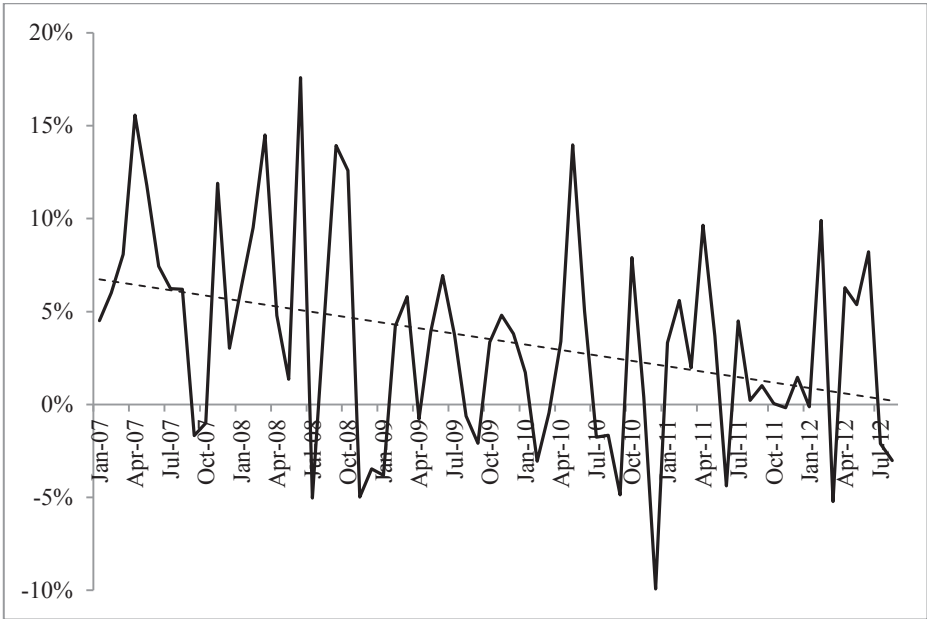


Figure 2.5: Forecast accuracy

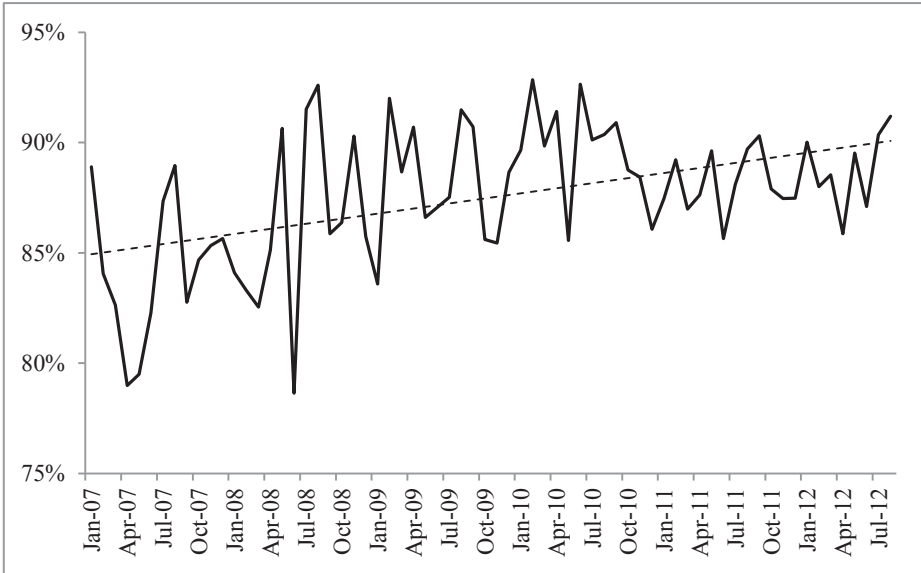


Figure 2.6: Accuracy of departmental and combined forecasts

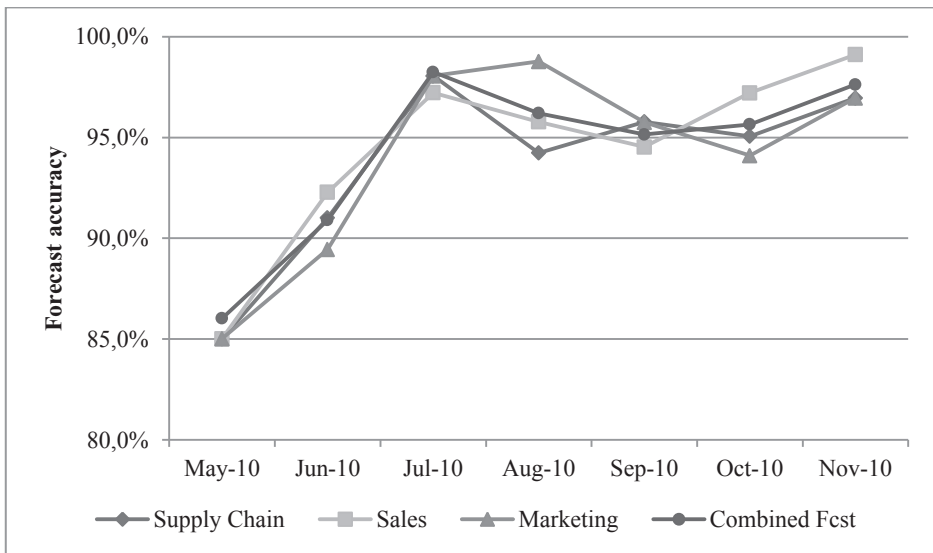
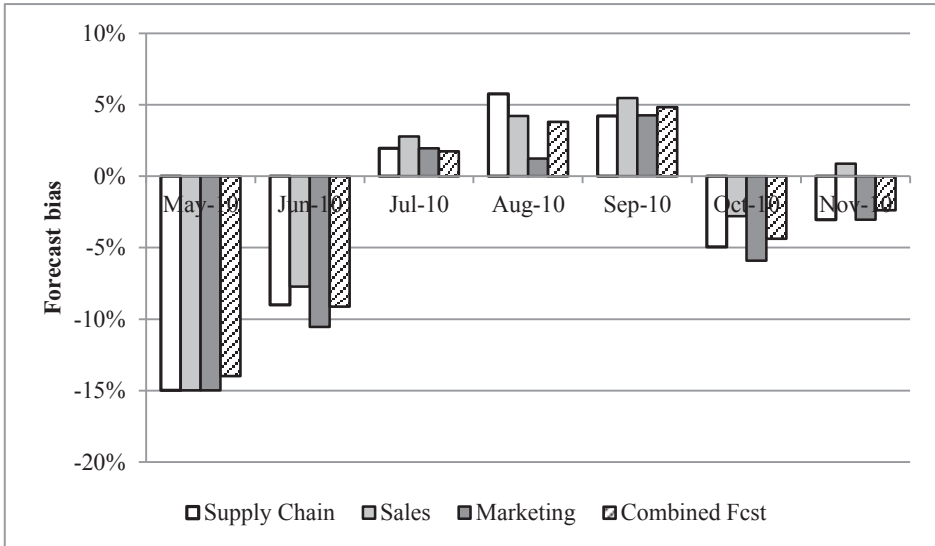


Figure 2.7: Bias of departmental and combined forecast



Unlike the change in forecast ownership, the introduction of the new methodology resulted in a change of actual behavior in such a way that all departments aimed at forecasting accurately rather than biasing the forecast in a direction that would suit departmental goals and agendas. The Planning manager noted in an interview:

“Sometimes, every player had a different type of argument about the number that was put on the table, but finally with this new methodology, you wanted to reach better accuracy because it increased your participation in the total forecast. So every person in the forecast review meeting was more conscious about what they were putting in the numbers. So, this was good for me. The behavior of the participants really changed.”

The increase in transparency and accountability through the new methodology to combine the departmental forecasts led people to forecast accurately. As the forecasts and previous forecast performance of each participant were shared and reviewed during the meeting, people would feel proud if their accuracy was good. The influence they could exert on the final forecast was not through manipulation of the departmental forecast in terms of its direction (very low or high), but in terms of its accuracy. Thus, we propose:

Proposition II. *A simple weighting scheme for the mathematical combination of judgmental and statistical forecasts based on past performance can increase forecast accuracy and reduce the structural forecasting bias inherent in functional differentiation.*

Another noteworthy result of the new forecasting methodology, which was not anticipated at the time of the implementation, was that the focus of the forecast review as well as S&OP meeting changed from short- to long-term orientation. Whereas, previously, mainly supply and capacity issues were discussed, the agenda now included topics such as new product launches, process improvement, business opportunities and the adherence to financial plans. The Planning manager described this unanticipated shift as follows:

“The demand review meeting really changed to a less conflict-laden meeting. And, of course, because of this, the same happened to the S&OP meeting. You have less subjectivity, less conflicts, and finally when you started to see results, everyone was saying: ‘Don't discuss about the number. Let's believe in the process. Let's focus on the drivers. And let's focus on the P'n'L [profit and loss]. And let's focus on all the type of things, and not whether the forecast is 105 or 110.’ So, there was more added value of the meetings.”

Our interviews revealed not only changes in actual forecasting behavior, but also in motivation after the implementation of the new forecasting methodology. We observed an increase in the commitment and engagement of the three departments. Whereas, during the early planning process the meetings lacked attendance, people now actively prepared and participated in the meetings. Especially the attendance, engagement and commitment of the Sales and Marketing directors in the S&OP meeting improved, essentially because now it had become more relevant for them. Whereas before the commitment to the forecasting process varied as a function of whether someone was a formal owner of the process or simply participating in the process, the non-owning participants now showed similar commitment without being assigned a formal form of ownership.

With the implementation of the new forecasting methodology, also the Marketing and Sales Departments felt that they had an influence on the final forecast. Whereas, people were previously dissatisfied with the final forecast because it was sometimes overruled and changed after the forecast review meeting, they now felt that they had a “*voice in the decision-making process*”. This was in sharp contrast to what a senior brand

manager noted before the implementation: *“I am not ok with the change of volumes in S&OP because all the previous analysis of hours that one does is just a waste of time.”* As the new forecasting methodology was also more transparent than before, everyone now had access to the information, and the assumptions behind the forecasts were openly discussed and evaluated. It also helped the Marketing and Sales Departments, who were previously less familiar with forecasting, to understand the consequences of inaccurate forecasts. Having more information and better knowledge about the forecasts enabled the Marketing and Sales Departments to develop feelings of ownership toward the forecast. Albeit not formally rewarded for participating in the forecasting process and providing accurate and timely input to the forecast review meeting, the Marketing and Sales Departments invested more time and energy into the forecasting process. All three departments now complied with procedures and perceived each others’ forecasts as more credible than before the implementation of the new forecasting methodology. The above examples suggest that the new forecasting methodology fostered ways for feelings of ownership to emerge. Therefore, our third proposition states:

Proposition III. *Involvement of the non-owning departments in the forecasting process can be achieved without assigning formal ownership and without changing formal incentives.*

2.7 Discussion

The purpose of the present research was to explore how forecast ownership and forecast combination can address forecast biases that are rooted in functional differentiation and incentive misalignment. By tracking two major change initiatives – the change in forecast ownership from the Marketing to the Supply Chain Department, and the introduction of a methodology that mechanically combined departmental forecasts into one composite forecast – we identified and described the potential benefits that these two factors may exert on the effectiveness of the forecasting process. Focusing on forecast ownership, we addressed an element of the forecasting process that was up until now largely ignored in the forecasting literature. By examining how well a forecasting methodology can address forecast biases and cross-functional conflict, we assessed the effectiveness of a forecasting process using evaluation criteria in addition to accuracy.

Our findings revealed that although the change in ownership led to an initial improvement in forecast accuracy, it had detrimental effects on the relationships between the functional areas involved in the planning process. It not only enhanced the organizational conflict rooted in functional differentiation, but also jeopardized the efficiency and credibility of the overall planning process. This highlights how a sole focus on improving forecast accuracy can backfire and create new, unforeseen problems. The change in forecasting methodology, on the other hand, with a more holistic focus on tackling the forecast biases of the functional areas, solved the conflict and led to a robust and credible process, producing accurate forecasts despite the continuing existence of diverging functional incentives. Furthermore, the study highlights how the involvement of those departments, that have no formal ownership over the forecast, can align the interests of owners and non-owners in the presence of diverging incentives and an absence of formal forecast ownership.

2.7.1 Theoretical implications

Our study makes several contributions to the literature. First, considerable research on behavioral forecasting focuses on the individual making the forecast (Lawrence et al., 2006). In many organizations though, the task of agreeing on a final composite forecast is often a cross-functional team effort. However, one of the dangers here (and in reality) is that of mixed motives (Van Lange, Joireman, Parks, & Van Dijk, 2013). In our study, we indeed found misaligned incentives and behavior on an individual as well as group level that endangered the cooperative forecasting process, such as the reluctance to share information, lack of commitment, and opportunistic behavior to pursue departmental goals rather than company-wide goals. Researchers have started to conceptualize supply chain alliances between firms as social dilemmas to explain why some alliances fail while others succeed (McCarter & Northcraft, 2007). Our study extends this line of research by focusing on intra-firm cooperation in the context of a collaborative forecasting process, and shows that social dilemma research not only helps understand supply chain partnerships *between* firms (e.g. McCarter & Kamal, 2013), but also supply chain collaborations *within* firms. Any attempt to improve forecast accuracy needs to consider

the effect that differential roles have on forecasting behavior and solve the social dilemma that decision-makers in the forecasting process face.

In this study, we explored one such attempt, the new methodology to mechanically combine departmental forecasts into one composite forecast. We showed that a simple weighting scheme based on past forecast performance was sufficient to induce a natural forecast accuracy incentive that was not part of the formal reward system. This nicely complements extant literature on forecast combination that often lacks the organizational context by exploring the organizational and psychological factors that shape a forecaster's behavior (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). The recently proposed salience-assessment-weighting (SAW) model (Rosenzweig & Critcher, 2014) similarly emphasizes the importance of weighting dimensions when individuals make forecasts. In the collaborative forecasting process described in this study, though, people had a vested interest in the outcome and the distortion of forecasts was motivated by departmental incentives. Thus, the new forecasting methodology applied previously agreed upon decision rules and impartially weighted the departmental forecasts, thus helped sidestep the influence of biases and improved forecast accuracy.

Second, by drawing on agency theory (Eisenhardt, 1989), we develop a novel theoretical construct called “forecast ownership” which we define as the planning and control over the forecasting process and its outcomes. While this assigned form of ownership may not necessarily be located in the Marketing or Supply Chain Department as in our case, shifting this formal responsibility from one group to another may produce similar effects as observed at BevCo. In line with agency theory, we assume that stakeholders in the forecasting process – in other words, forecast owners and non-owners – act according to their incentives and aim at maximizing individual benefits. However, we depart from the traditional view of agency theory by showing that assigning formal ownership is not the only way to encourage commitment from owners, and more importantly non-owners, and aligns diverging interests and motivates forecasting behavior that benefits the overall organization.

So far, most research on psychological ownership has focused on the organization or particular jobs as targets of ownership (e.g. Mayhew, Ashkanasy, Bramble, & Gardner, 2007). We suggest that feelings of ownership may also emerge with respect to a forecast

and that the Marketing and Sales Departments, who did not possess formal ownership, exhibited a form of psychological ownership. The new methodology to combine departmental forecasts gave people the opportunity to exercise control over decisions that impacted the forecast, created knowledge about the forecast and a feeling of being associated with the forecast. Consequently, also the Sales and Marketing Departments, formally non-owners, invested themselves into the forecast and devoted significant energy to the process because they experienced the forecast to be theirs. As such, our study highlights the need to understand both formal as well as psychological ownership and how they affect behavior in cross-functional planning processes.

Psychological research suggests that ownership not only manifests itself as a legal phenomenon, but “operates from both a formal and a psychologically experienced platform” (Pierce, Rubinfeld, & Morgan, 1991, p. 126). The concept of psychological ownership is defined as a “state in which individuals feel as though the target of ownership (material or immaterial in nature) or a piece of it is ‘theirs’” (Pierce, Kostova, & Dirks, 2001, p. 299). Accordingly, psychological ownership nurtures the feelings of efficacy and effectance, helps people to define themselves, and satisfies the need for territoriality and security (Pierce et al., 2001). Psychological ownership emerges, if people experience having control over the target of ownership, intimately know the target of ownership, and invest themselves into the target of ownership (Pierce et al., 2001). Unlike earlier research, recent studies propose that feelings of ownership can arise in the absence of formal ownership (e.g. Brown, Pierce, & Crossley, 2014).

2.7.2 Managerial implications

One question that keeps managers in organizations awake at night is the question of which department should own the forecast (Smith & Clarke, 2011). Although the present study is one of the first to illuminate the concept of forecast ownership based on a real-life case study, it does not attempt to answer this particular question. Instead, it addresses the broader problems associated with forecasting in organizations on how to achieve accurate demand forecasts and shows that forecast ownership, in fact, is a double edged sword with both positive and negative consequences, if the social context that surrounds the forecasting process is ignored.

Assigning formal forecast ownership to a particular department means assigning formal responsibility and accountability for the forecast and the results of the forecasting process. In many organizations, there is a lack of such clear ownership and the responsibilities are diffused across the organization (Adebanjo & Mann, 2000), but even if there is a clear owner, all relevant stakeholders in the process have varying interests and incentives that may be at odds with the organizational goal of producing accurate forecasts. This study shows that assigning forecast ownership to the department that assumingly has the highest vested interest in producing accurate forecasts (in our case the Supply Chain Department) may improve forecast accuracy in the short-term. However, it cannot eliminate the systematic forecast biases to over- or under-forecast that are inherent in functional differentiation. Even worse, shifting forecast ownership for the sake of forecast accuracy can create unforeseen additional tension between those that possess formal ownership and those that have lost it, and jeopardize the entire planning process in the long run. This highlights the need for tackling dysfunctional behavior rather than focusing on forecast accuracy alone.

A more holistic approach in this study proved to be the introduction of a new forecasting methodology to mechanically combine departmental forecasts into one composite forecast using weights based on past forecast accuracy. Such an approach that underscores the importance of forecasts can naturally motivate all departments (independent of their departmental goals) to forecast accurately (McCarthy Byrne, Moon, & Mentzer, 2011). As a result, dysfunctional, biased forecasting behavior can be eliminated, forecasts become more accurate and forecast variability decreases leading to better predictability of the forecasts and a more stable and robust forecasting process. As such this approach offers a viable alternative in situations in which changing formal incentive systems is not a feasible solution. Similarly, it is important for managers to understand that involvement and commitment from non-owning stakeholders in the forecasting process can be achieved through creating a feeling of ownership that goes beyond formally assigned ownership. Giving people the opportunity to have a say in the forecast, to invest time and energy in the forecasting process, and disseminating information and knowledge about the forecast and the forecasting process are all means to create such psychological ownership over the forecast. Finally, as the problems of owner

and non-owner and misaligned incentives are not exclusive to supply chain planning processes our findings generalize to other cross-functional processes in organizations in which goal-conflicts are detrimental to performance.

2.7.3 Limitations and future research

Despite its theoretical and practical contributions the most obvious limitation of the present study is that the observations are based on a single case study, and that their statistical generalization can therefore be questioned. True as this may be, the general strength of case studies is to build theory. Just as others have done for various topics in the operations research domain (e.g., Barratt & Barratt, 2011; Bendoly & Cotteleer, 2008; Heikkilä, 2002), we were nevertheless able to offer valuable insights for directing future research into the role of forecast ownership. As such, the research site represents an example of a supply chain planning process that is common place in companies in the FMCG industry. Hence, our results have the potential to be informative about people's forecasting behavior in a wider range of similar settings (Yin, 2009).

As the collaborative forecasting process is increasingly common in many organizations and poses similar challenges of aligning all the stakeholders in the process, our case study findings can be considered representative. However, more case-based research should further develop and refine the concept of forecast ownership and elaborate on the dynamics between owners and non-owners when forecast ownership changes. Future studies should also consider collecting data from companies in which the ownership structure differs from the presented case, if the purpose is to improve generalizability. For example, the forecast may be owned by neither Marketing nor Supply Chain, but another functional group such as Finance or a neutral entity (Oliva & Watson, 2011), which could change the observed behavior and social context.

When access to real organizations is difficult to gain, forecast tournaments with students or managers may offer a good alternative to test theoretical propositions (Tetlock, Mellers, Rohrbaugh, & Chen, 2014). Moreover, such competitions have the potential to help answer research questions that could otherwise not be answered, for example when certain factors should be altered to explore their effect on forecasting behavior. As this study shows, the social context and more specifically the social dilemma that surrounds the

forecasting process may have a huge impact on people's behavior. An avenue for future research would be to (artificially) design the social context around the forecasting process by altering departmental goals, ownership structures or forecasting methodologies. Vast research on social dilemma shows that people generally differ in their sensitivities toward cooperation or conflict in such mixed motive situations (e.g., Parks, Joireman, & Van Lange, 2013). Hence, investigating inter-individual differences in forecasting tasks warrants further research.

Albeit a retrospective case, the quasi-longitudinal design of our case study allowed us to observe the phenomenon and the effect of the change initiatives over time. As this was a first attempt to investigate how forecast ownership and forecast combination affect forecast behavior in a supply chain planning process, the main contribution of this study lies in its level of detail, generating rich data, and suggesting propositions that warrant further investigation.

Conclusion. Summing up, our study shows that assigning forecast ownership to a department that is aware of the importance of accurate forecasts is not sufficient to change biased forecasting behavior that is rooted in incentive misalignment. A methodology to combine forecasts that increases transparency and accountability and creates a sense of ownership also among non-owners in the forecasting process can align interests in the presence of diverging incentives.

Appendix A: Example interview protocol

1. Information about the CBU
 - 1.1. Product
 - 1.2. Customers
 - 1.3. Suppliers
 - 1.4. Organizational structure (especially department structure, parties involved in forecasting)
 - 1.5. The division in the "picture"
 - 1.6. The business environment back then
2. Personal background
 - 2.1. How long had you been with BevCo?
 - 2.2. In what position?
 - 2.3. What were your main responsibilities?
3. The forecasting process
 - 3.1. Describe the process that was initially in place. (each activity and step it entailed)
 - 3.1.1. Involved people, departments in the forecasting process
 - 3.1.2. Time horizon
 - 3.1.3. Forecast cycle time
 - 3.1.4. Times generated and updated
 - 3.1.5. Tools
 - 3.1.6. Inputs and outputs
 - 3.1.7. Meetings
 - 3.1.8. Performance measures used for the forecast and for the involved parties
 - 3.2. How would you describe the relationship between the three parties in the old process?
 - 3.3. How effective was the process? Performance?
 - 3.4. What were major issues with the process? (examples)
 - 3.5. How did those issues affect performance? (examples)
 - 3.6. Recall disruptions and how you dealt with them.

- 3.7. Were there previous attempts to solve these issues/work around these issues?
4. The change process
 - 4.1. The business environment at the time of the change
 - 4.2. What was your position at the time the change took place?
 - 4.3. What was your role in the change process?
 - 4.4. How did you approach the change/implementation process?
 - 4.5. Who was involved?
 - 4.6. Who was affected?
5. The new forecasting process
 - 5.1. Describe the new forecasting process. (for every change, new activity, new step, enquire about the rationale behind it)
 - 5.1.1. Involved people, departments in the forecasting process
 - 5.1.2. Time horizon
 - 5.1.3. Forecast cycle time
 - 5.1.4. Times generated and updated
 - 5.1.5. Tools
 - 5.1.6. Inputs and outputs
 - 5.1.7. Meetings
 - 5.1.8. Performance measures used for the forecast and for the involved parties
 - 5.2. Name THE one or two key changes.
 - 5.3. How did the new process address some of the issues of the initial process?
 - 5.4. How did it affect Marketing?
 - 5.5. How did it affect Sales?
 - 5.6. How did it affect Operations?
 - 5.7. How would you describe the relationship between the three parties in the new process?
 - 5.8. How effective was the new forecasting process?
 - 5.9. Recall disruptions and how you dealt with them

Appendix B: Coding protocol

Key theme	Definition	Example interview fragments
Meetings	Forecast review, S&OP or other meetings; issue related to agenda/scope of topics; preparation and attendance	“The meeting was very inefficient because nobody knew in advance what the others were about to bring to the meeting.”
Forecast bias/accuracy	A forecast is biased, if it is too low or too high compared to actual demand. Related to accuracy, i.e. how close actual demand is to the forecasted demand.	“It was very clear for us that the forecast was always bigger than the actual.”
Commitment	Promise to do something; being dedicated to a cause or activity; feeling of responsibility for something	“Some directors go to the meeting. Others don’t.”
Decision-making	Choosing a course of action among several alternatives; individual or joint decision-making	“Before we had to spend one hour to agree on a number for the two main SKUs.”
Forecast creation	The way of arriving at a forecast: 1. quantitative, statistical forecast, 2. qualitative, judgmental forecast	“It’s really a homemade way of arriving at the forecast for each of the departments.”
Effectiveness	Operational effectiveness, but also meeting effectiveness; degree to which objectives are achieved and the extent to which problems are solved in comparison to the resources (time and labor) invested	“We suddenly counted on much more time. Time to discuss the process itself or product launches.” “There was more added value in the meeting.”
Formalization	Extent to which the work is governed by rules and procedures	“The process was quite disorganized before I took over the position.”

Coding protocol (continued)

Key theme	Definition	Example interview fragments
Personal relationships	Ties between individuals	“Sales and Marketing need to work very close together.”
Organizational structure	Roles and responsibilities within the company; reporting lines	“We have a lot of rotations between the departments.”
Objectives	Goals that define a function’s purpose	“In the case of Supply Chain, we really wanted to have a good forecast accuracy for the sake of our operations because we knew the impact on our stocks and the production plan.”
Ownership	Assignment of final responsibility/authority for the forecast	“The forecast was owned by Marketing. Supply Chain didn’t have a say. We would just receive the forecast as a fact.”
Horizon	Orientation towards short- or long-term planning and objectives	“Sales was short-term oriented because they executed the Marketing plans. Long-term orientation was more a responsibility of Marketing and Supply Chain.”
Trust	Believe in the truth, reliability, integrity or ability of someone/something	“We have less subjectivity, less conflicts, and finally, when you start to see results, everyone was really saying ‘don’t discuss about the number, let’s believe in the process’.”

Coding protocol (continued)

Key theme	Definition	Example interview fragments
Formal incentives	Rewards that are associated with roles/jobs within the company and that influence behavior of individuals and groups	“If you count of a too optimistic forecast, then you will get a too optimistic, too challenging sales target which then makes you less likely to get your variable salary.”
Information sharing	Exchange of (timely, complete, accurate) data and information between individuals and departments	“They would somehow create information to bring to the meeting, but it was not in a structured way and it was not shared with the other parties before the meeting.”
Transparency	Lack of hidden agendas; availability of full information required for collaboration and joint decision-making	“The key point is to explain why you forecast that number, for example because I am planning a Marketing campaign.”
Feedback	Results/output of a decision or action are used to modify the next decision/action in order to achieve desired result	“The first thing we would upload in the shared database to be shared with the other stakeholders was the forecast accuracy from the previous month, so as to take that into account when each of the areas had to prepare their forecast.”
Decision support (tools)	Computer system designed to inform decision-making	“The key point of this tool is that it allows you to arrive at a consensus in a peaceful way.”
Seasonality	Periodic, repetitive pattern in sales levels where most or all sales originate in a particular season	“The consumption of all these beverages has a huge peak during summer. And then in winter, it really goes down.”

Coding protocol (continued)

Key theme	Definition	Example interview fragments
Power	Ability to cause or prevent an action or decision	“We need knowhow in this meeting and we need empowered people because we have to take decisions and it’s important to have a clear seniority there.”
Stakeholder involvement	Involving individuals affected by the change in the various phases of the change process	“I created interviews with them in a structured way to get to know their perception of the existing process.”
Economic/ political situation	Factors that have an impact on how the business operates	“The government would limit the price increments that you could do. That was tough as most of our raw materials and packaging are internationally sourced.”
Need for change	Creating an awareness of the reasons to change	“We took some time to really understand what the best option for the forecasting process is. But to really have an outstanding result, you will need to change the process.”

3 The Generation of Negotiated Demand Forecasts: Effects of Managerial Role, Social Value Orientation and Agent Type

The lack of integration of sales and operations is an important shortcoming in judgmental forecasts, potentially undermining their accuracy. Using insights from research on negotiation and social dilemmas, we posit that departmental affiliation within a company shapes a forecaster's perception about forecast negotiations. Experimental results confirmed our prediction that forecasting behavior is moderated by a forecaster's social value orientation – an individual disposition towards cooperation or conflict.

3.1 Introduction

The generation of demand forecasts is an important process in most organizations. As forecasts are used for numerous supply chain planning decisions, their accuracy directly impacts capacity, inventory levels, customer service levels, and the overall match between supply and demand, and consequently a company's short- and long-term profitability (Hendricks & Singhal, 2009). Although a wide variety of quantitative forecasting methods are available to facilitate forecast generation, human judgment is still an indispensable decision aid in practice (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). However, the value of human judgment in adjusting forecasts depends on the credibility of that judgment. Forecasts are often overly optimistic across various industries (Cohen, Ho, Ren, & Terwiesch, 2003; Lee, Padmanabhan, & Whang, 2004). Moreover, forecasting processes usually cross functional boundaries within companies and include different departments, such as marketing, sales, production and operations (Lawrence, O'Connor, & Edmundson, 2000). Different perspectives, dispersed knowledge, as well as diverging interests and incentives that determine organizational behavior, may also shape forecasting behavior such that different departments set the forecast in line with these incentives. This makes the task of inter-departmental forecast negotiations highly challenging.

Interestingly, vast behavioral research on negotiation and social dilemmas shows that people in general differ in their subjective perceptions of so-called negotiated outcome interdependence (Halevy & Katz, 2013) and in their individual sensitivities towards

cooperation and conflict (Parks, Joireman, & Van Lange, 2013) that influence how people resolve the conflict inherent in social dilemmas. Social value orientation (SVO), as an individual difference in how people evaluate outcomes for themselves and others (Messick & McClintock, 1968; Van Lange & Kuhlman, 1994), has received a great deal of attention. The vast experimental SVO research shows that prosocial individuals are more likely than proself individuals to cooperate in a variety of social dilemmas (for reviews, see Au & Kwong, 2004; Balliet, 2010; De Dreu, Weingart, & Kwon, 2000; Van Lange, De Cremer, Van Dijk, & Van Vugt, 2007). The present research applies these insights to negotiated demand forecasts, and focuses on the extent to which departmental affiliation within a company influences forecast and negotiation behavior in forecast meetings. In addition, we explore the related issue, if and to what extent the sometimes detrimental effect of departmental affiliation on forecast accuracy can be attenuated by a forecaster's individual disposition towards cooperation and conflict. A major contribution of this research is that we study the relationships between a forecaster's departmental affiliation and social motives in an experimentally designed social dilemma in the forecasting context. Our focus on the relationship between departmental affiliation, social motives and forecasting behavior significantly extends our theoretical understanding of forecasting behavior in interdependent situations.

We proceed in Section 2 by providing the theoretical background as well as research hypotheses underlying this research. We then describe the experimental design and procedure in Section 3, followed by the results in Section 4. Finally, we summarize our findings and conclude this article with suggestions for future research opportunities in Section 5.

3.2 Theoretical background

Despite the existence of sophisticated decision support systems, it is common practice in companies to adjust statistical forecasts based on human judgment (Fildes et al., 2009). Among others, adjustments may simply be made to incorporate additional information that was not built into the time-series history (Fildes & Goodwin, 2007). This is unfortunate, because human judgment can be erroneous due to cognitive limitations (Tversky & Kahneman, 1974) as a result of which statistical forecasts may become biased

after judgmental modification. Several recent studies have reported behavioral anomalies related to demand forecasting and examined ways to improve decision-making in this context (e.g. Kremer, Moritz, & Siemsen, 2011; Lee & Siemsen, 2013). In their classic behavioral study of the newsvendor problem, Schweitzer and Cachon (2000) suggested that separating the forecasting and inventory setting task can improve decision-making. Similarly, Lee and Siemsen (2013) showed that de-biasing strategies improve forecast performance when the task was decomposed into point forecasts, uncertainty judgment and service level decisions. This seems to suggest that it is important to examine the different components of a decision, in our case forecasting demand and setting the production quantity, separately.

A central challenge in forecasting is to pool the decentralized knowledge about demand and supply that exists throughout the company and is often biased by human judgment (Kremer, Siemsen, & Thomas, 2012). In organizational forecasting, each member represents a different department subject to potentially diverging incentives and motivations. Such differentiation generates conflicts over differing expectations, preferences, and priorities with respect to how the matching of demand and supply should be accomplished (Shapiro, 1977). Importantly, an emerging research in operations management now indicates that the forecasting process is especially influenced by a forecaster's departmental role and managerial pressure (Syntetos, Nikolopoulos, Boylan, Fildes, & Goodwin, 2009). In their case study, Oliva and Watson (2011) describe a consensus forecasting process that includes various departments and that illustrates that functional biases can indeed have a major impact on forecast performance. Kuo and Liang (2004) have shown that departmental roles indeed influence forecasts, even if different departments possess the exact same information. Another study examining the effect of departmental roles on forecasting showed that differential departmental roles, that is, being part of a Marketing or Production Department, distorted (i.e., biased) judgmental forecasts in line with organizational incentive structures (Önkal, Lawrence, & Zeynep Sayim, 2011). It therefore makes sense to assume that when forecasts are connected to functional targets, forecast accuracy may suffer as a result of biased forecast behavior. A production manager, aiming at keeping inventory levels low, may provide lower forecasts, while a product manager concerned with sufficient product availability, may set forecasts high to

avoid lost sales. Thus, being a member of a specific (organizational) department may have an impact on someone's actual forecasts and the planned production quantity that is communicated to another department. We thus predict the following:

Hypothesis 1: Managerial role impacts forecasting behavior such that sales managers will be overoptimistic in their forecast and inflate the communicated production quantity whereas operations managers will be cautious in their forecasts and deflate the communicated production quantity.

In order to solve the problem of forecast manipulations in inter-organizational settings, repeated interaction (Ren, Cohen, Ho, & Terwiesch, 2010) or contract design (e.g. Cachon & Lariviere, 2001; Özer & Wei, 2006) have been suggested to align incentives. From a more behavioral perspective, differential goals and interdependences affect an individual's motivations and decisions in operations management settings in general (Bendoly, Croson, Goncalves, & Schultz, 2010) and in the forecasting context in particular (Özer, Zheng, & Kay-Yut Chen, 2011).

Within social dilemma research, social value orientation is an important personality measure that in general refers to the weight people attach to their own outcomes relative to those of others in an interdependency situation (Messick & McClintock, 1968; Van Lange & Kuhlman, 1994). As an individual difference measure, SVO captures the extent to which people deal with conflict in a social dilemma, and opt for choices that are in their own or rather than collective interest. A variety of social motives can be distinguished (Murphy & Ackermann, 2014), but the individualistic (non-cooperative) and the prosocial (cooperative) orientations are especially relevant in negotiations. In fact, social motives have been shown to have a major impact in a negotiator's strategy (De Dreu et al., 2000; Pruitt & Carnevale, 1993). When people are low on SVO, thus individualistic, non-cooperative, they attach importance to maximizing their own outcome; when people are high on SVO, thus prosocial, cooperative, they are concerned with achieving high outcomes for themselves and other interdependent people (Murphy, Ackermann, & Handgraaf, 2011; Nauta, Dreu, & Vaart, 2002; Parks et al., 2013). Overall, previous research has shown that prosocial individuals exhibit more cooperation than proself

individuals (Beersma & De Dreu, 2002; De Cremer & Van Lange, 2001; De Dreu & van Lange, 1995)

Of particular relevance to the present discussion is the research by Nauta et al. (2002) on problem solving behavior of manufacturing, planning and sales employees during interdepartmental negotiations. This research suggests that people high on SVO in organizational settings are inclined to also consider the goals of other departments in their decision-making. For example, manufacturing employees would not only be concerned with efficiency as their primary goal, but also care about service which is a particular concern of a Sales Department. On the other hand, people low on SVO are inclined to ignore the consequences of their decisions on another department. For example, sales employees may exclusively focus on customer service and ignore the impact that certain sales decisions may have on operational efficiency, which is a primary goal for the Manufacturing and Planning Departments. Interestingly, SVO also makes a difference for adopted negotiation strategy in inter-departmental negotiations, and the extent to which there is a match or mismatch between how to approach the social dilemma (see Halevy & Katz, 2013, for a more abstracted observation; Rhoades & Carnevale, 1999). Applied to negotiated forecasts, it therefore makes sense to assume that – taking the organizational role into account – a decision maker’s own motivational orientation, that is, whether she is high or low on SVO, will affect forecasting behavior in such a way that sales and operations managers low on SVO are particularly concerned with their own departmental goals and therefore make forecast and production decisions to ensure that departmental goals are reached. We thus predict the following:

Hypothesis 2: Managerial role and SVO interact such that forecasts of sales and operations managers will be more biased and production quantities more inflated (versus deflated) when a decision-maker’s SVO is low rather than high, respectively.

Major components of organizational forecasting are the aggregation of individual forecasts into one number, and the negotiation process during which forecasts are adjusted in order to reach a consensus forecasts. Negotiation, though, involves a fundamental

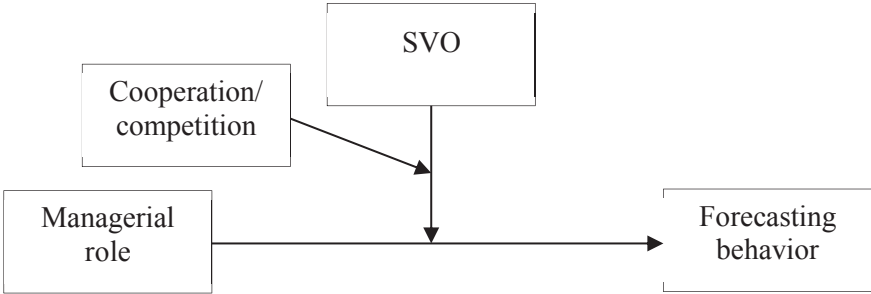
tension between a need to cooperate or to compete in order to achieve their goals – that is, negotiation is a typical social dilemma situation, in which outcomes result from interdependencies between parties (De Dreu, 2010; Parks et al., 2013). This begs into question what induces participants to change their initial position and thus *de-bias* forecasts and improve forecast accuracy. The behavioral research into social dilemmas deviates from the economic alternative (cf. Ostrom, 1998) in the sense that the extent to which someone is prone to cooperate or compete with someone else depends on that person's willingness or motivation to do so. In a cooperative approach, one would usually seek win-win solutions and aim at maximizing common outcomes. In a competitive approach, one would usually pursue one's personal goals (Parks et al., 2013). Similarly, research on the reciprocity of cooperation or conflict has shown that cooperative and competitive individuals differ in their expectation about the cooperative motives of their negotiation partner (Lumsden, Miles, Richardson, Smith, & Macrae, 2012; Parks & Rumble, 2001; Van Lange, 1992; Weingart, Brett, Olekalns, & Smith, 2007). Applied to the forecasting process, an accurate forecast represents a common goal, while functional incentives such as minimizing lost sales or obsolescence costs represent individual goals. People react differently in negotiations depending on the perceived competitiveness or cooperativeness of their counterpart (Burnham, McCabe, & Smith, 2000). However, because perceptions of outcome interdependence are a function of someone's affiliation (as in general shown by: Halevy & Katz, 2013), we predict that also in forecast negotiations, people show the tendency to over- or under-forecast (and subsequently inflate or deflate) their forecasts more extremely depending on their managerial role, social value orientation and cooperativeness of the negotiation counterpart. We thus predict the following:

Hypothesis 3: Managerial role and negotiation strategy interact such that forecasts will be less biased in a cooperative forecast negotiation, but more biased in a competitive forecast negotiation.

Figure 3.1 graphically presents the model for the present study. The hypotheses were put to the test in a laboratory experiment, which gave us full control over our

experimental conditions and the experimental task, and allowed us to measure participant’s forecasting behavior with a relatively high degree of objectivity.

Figure 3.1: Proposed model experiment 1



3.3 Method

Participants and Design

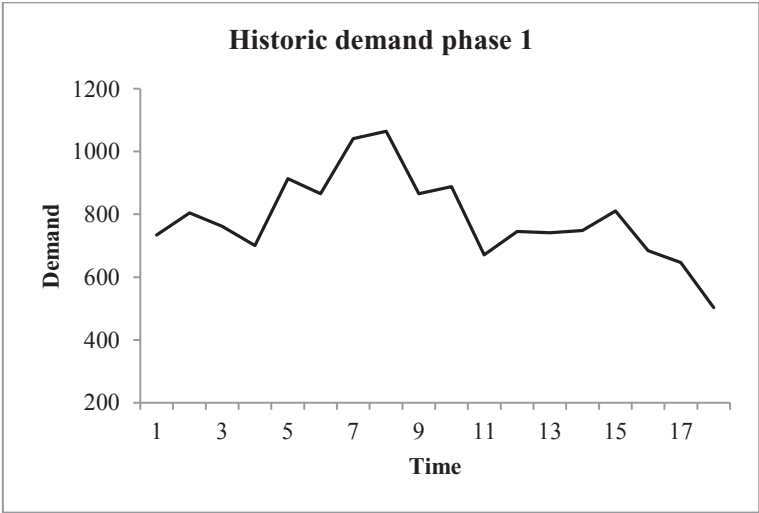
Participants were randomly assigned to the conditions of a 2 (managerial role: sales, operations) X 2 (agent type: cooperative, competitive) mixed factorial design to which SVO was added as covariate. The initial sample consisted of 111 participants (55 men, 56 women, *M* age = 23.09 years, *SD* = 6.23). The majority (97 participants) was from a Dutch university who received course credits for participation in a laboratory experiment. The remaining 14 participants were professionals who completed the experiment as part of an in-house company training. There were no differences between the two sub-groups in terms of SVO or forecasting behavior, hence we treated them as one group in further analyses. The data of a small fraction of participants (*N* = 7; 6.31%) were excluded from analyses. Six participants were excluded because they answered both manipulation check questions regarding their role in the experiment incorrectly, indicating that they misunderstood the role assigned to them, which was also shown in their random answers to the experimental task. One participant was excluded from the analysis because of an unusual SVO categorization which seemed to suggest a striking lack of interest in the assignment. This resulted in a final sample of 104 participants, i.e. 90 undergraduate students and 14 professionals (53 men, 51 women, *M* age = 23.20 years, *SD* = 6.37).

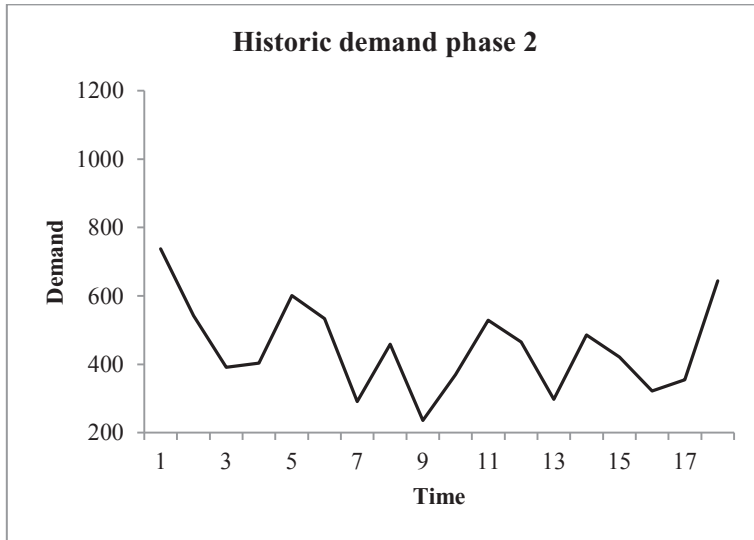
Materials and Procedure

At the beginning of the experiment, participants received instructions for the experimental task containing the role manipulations, together with background information about the company, a producer of fresh juice for which they presumably worked as a demand planner. Participants were instructed to forecast demand for the product for the coming month (one month equaled one period), and to provide an input, i.e. a production quantity, to a planning meeting with another demand planner in each period. The forecasting task was thus separate from the participation in the planning meeting.

The experimental task consisted of two separate phases in which the participant was provided with 18 periods of historic demand data as shown in Figure 3.2. The demand distribution was a random walk with noise and our demand environment resembled a non-stationary (high change, high noise) demand pattern. This is common in research on forecasting as it captures many real-life situations as opposed to stationary demand patterns that do not reflect real life processes very well (Gardner, 2006; Makridakis & Hibon, 2000).

Figure 3.2: Historic demand data for phase 1 and 2





In the first phase, participants were asked to provide per period: (1) a private forecast estimate of expected demand that only they could see, and (2) a separate production quantity, which was used as input for the planning meeting, and shared with the other demand planner. At the end of each period, participants could see the consensus forecast of the planning meeting, which was the average of their own and the other demand planner’s production quantity, and determined the final production quantity. In each period, the participant could observe actual demand after decision making and reception of feedback about forecast accuracy, lost sales, obsolete units, company profit and individual performance score. For phase two, participants were informed about a change in the company’s policy regarding forecast generation – a three-round negotiation process would be introduced into the planning meeting. Now, after submitting their production quantity, participants could also see the other demand planner’s production quantity and decide whether or not to adjust their own input. Upon completion, participants were directed to an online post-questionnaire including manipulation checks and SVO. Participants were debriefed at the end of the experiment.

Manipulation of managerial role. Participants received instructions that either described their role as sales or operations manager, and aimed at triggering the adoption of role-specific behavior as follows:

- (1) You are an operations manager. Your job is about getting work done quickly, efficiently, without error, and at low cost. Minimizing costs is a key responsibility of this position. Unsold juices are obsolete at the end of a period, as they are no longer fresh. A high level of obsolescence means that you will have to destroy products that you produced and for which you employed resources. As a result you will have incurred obsolescence costs, namely 1€ production cost for every unsold bottle of orange/mango juice. Keep that in mind when providing input for the planning meeting!
- (2) You are a sales manager. Maximizing customer service levels and increasing sales are key responsibilities of this position. Sales involves meeting the sales targets of the organization through developing sales plans that identify the sales possibilities and future market conditions. Sales are, of course, a launch pad for profit. If there are not enough products available, *Sunrise* incurs cost of lost sales and profits are foregone. Lost sales cost you 1€ for every bottle of unfulfilled demand. Keep that in mind when providing input for the planning meeting!

Participants were evaluated based on how well they achieved the goals of their particular function – i.e., minimized lost sales for the sales manager and minimizing obsolete products for the operations manager. These incentives were chosen based on the distinct costs each function incurs from a mismatch between demand and supply (Fisher, 1997).

Manipulation of agent type. Depending on managerial role, the other demand planner in the planning meeting, in reality a programmed computer agent, possessed the opposite role – i.e., participants with a sales manager role encountered an operations manager in the meeting and participants with an operations manager role encountered a sales manager in the meeting.

Phase 1. In the first phase, the agent type was held constant for all participants in terms of its forecasting behavior. This means that for each agent type – sales or operations – there was a predetermined sequence of production quantities that the agent followed.

Phase 2. In the second (negotiation) phase, the computer agent was programmed to respond more or less cooperatively as indicated by the level of concessions. A cooperative agent was more willing to move closer towards the optimal point of the participant in

terms of forecast accuracy than a competitive agent who stayed closer to its own optimal point. Participants were informed of the managerial role of the other demand planner, but not of the demand planner’s negotiation strategy.

The planning meeting was simulated as an electronic negotiation in which negotiation partners did not meet face-to-face. Electronic negotiations in general do not suffer from efficiency loss in terms of integrative agreements compared to face-to-face negotiations (Croson, 1999). In fact, the level of cooperation, for example mutual disclosure, trust and reciprocity, is higher in face-to-face negotiations compared to negotiations through mediated channels (McGinn & Croson, 2004). Also in our setup, electronic negotiation with the agent did not automatically lead negotiators to behave cooperatively: our electronic negotiation context was characterized by low social awareness to control for the confounding effect of high levels of social awareness that tend to increase prosocial (cooperative) motives in negotiations (De Dreu et al., 2000).

Social value orientation. The SVO slider measure (Murphy et al., 2011) was used to assess participants’ social value orientation. The SVO slider measure has been demonstrated to yield high internal consistency, test-retest reliability and construct validity (Murphy et al., 2011), to outperform other SVO measures such as the 9-Item Triple-Dominance Measure or the Ring Measure on this metrics, and to overcome some limitations of previous SVO measures (Murphy & Ackermann, 2011). The measure was introduced to the respondent as a resource allocation task in which the decision-maker has to indicate her preference how a joint payoff should be distributed between her and another unknown person; see Table 3.1 for two example items.

Table 3.1: Two example items of the SVO slider measure

	Option	1	2	3	4	5	6	7	8	9
Item 1	Self	85	85	85	85	85	85	85	85	85
	Other	85	76	68	59	50	41	33	24	15
Item 2	Self	85	87	89	91	93	94	96	98	100
	Other	15	19	24	28	33	37	41	46	50

(source: Murphy et al., 2011)

Participants were asked to indicate their preferred option to allocate the gain between oneself and another. Based on six primary items in the slider measure, participants were described as high or low scorers on SVO. These categories were derived from a computed SVO angle. First, the mean of the payoff allocations for self (\bar{A}_S) as well as for the other (\bar{A}_O) were calculated. Then, 50 was deducted from both means (R. O. Murphy et al., 2011). In order to arrive at a single index of an individual's social value orientation, the inverse tangent of the means was computed:

$$SVO^\circ = \arctan(\bar{A}_O - 50)/(\bar{A}_S - 50) \quad (1)$$

The idealized SVO types can be derived from the boundaries between the angles – i.e. altruists would have an angle greater than 57.15° , prosocials would have angles between 22.45° and 57.15° , individualists would have angles between -12.04° and 22.45° and competitive types would have an angle less than -12.04° (Murphy et al., 2011). For the analyses reported in the present study, we used the continuous SVO.

Dependent measures

Forecasts. We recorded participants' forecasts for each period and phase. In order to compare groups, we averaged an individual's forecasts for each phase, where for phase 1, *FC1* denotes the average forecast of round 1 to 10 and for phase 2, *FC2* denotes the average forecast of round 11 to 20.

Production quantities. We recorded participants' production quantities *Q* for each period and phase. As participants entered only one production quantity as meeting input in phase 1, we proceeded with calculating the average production quantity *Q1* for phase 1 as described above. For phase 2, we averaged an individual's initial production quantities (*Q2.1*) that were entered at the beginning of the negotiation and the final production quantities that were entered at the end of the negotiation (*Q2.4*).

Adjustment score. We also calculated an adjustment score for each period and phase that indicated to what extent participants inflated or deflated their private forecasts to the communicated production quantity. For sales, an adjustment score of 1 indicated an inflated production quantity. For operations, an adjustment score of -1 indicated a deflated

production quantity. An adjustment score of zero would indicate no difference between forecast and communicated production quantity.

Concession score. Finally, for the negotiation phase, we recorded concession behavior from the first to the final negotiation cycle in each period, indicating whether participants moved towards or away from their negotiation counterpart, the computer agent. For sales, a concession score of 1 indicated concessions in the direction of operations – i.e., moving towards operations’ optimal point. For operations, a concession score of -1 indicated concessions in the direction of sales – i.e., moving towards sales’ optimal point.

3.4 Results

Manipulation Checks

Our manipulation of managerial roles was intended to affect participant’s forecasting behavior following particular functional incentives. To check whether our manipulation had been successful, we asked participants two questions about their assigned role in the forecasting meeting. The two items were: “What was your specific role in the forecasting meeting?” and “According to the instructions, which manager were you?” In the sales condition, 94.8 percent of participants answered both role-related questions correctly, while in the operations condition, 95.7 percent of participants answered those questions correctly. A *t*-test revealed significant differences for the manipulation check for sales ($M = 1.03$, $SD = 0.11$) and operations ($M = 1.98$, $SD = 0.10$), $t(102) = -44.67$, $p < .01$.

Our manipulation of agent type was intended to affect participants’ perception of the cooperativeness of their negotiation counterpart. To check whether participants indeed perceived the agent’s negotiation behavior as such, we asked participants to what extent they had perceived their counterpart in the negotiation as cooperative, on a five-point rating scale ranging from 1 (not at all), to 5 (very much so). A *t*-test revealed that participants in the cooperative agent condition perceived the agent as more cooperative ($M = 3.79$, $SD = 0.94$) than participants in the competitive agent conditions ($M = 3.37$, $SD = 0.89$), $t(102) = 2.37$, $p < .05$. This indicated that both manipulations indeed triggered managerial role and agent type, respectively.

To test our three hypotheses, we used conditional process analysis (Hayes, 2013). All hypotheses were tested with the inclusion of bootstrap estimates and 95% confidence intervals, and with the inclusion of the control variables age, gender and forecasting experience. None of these control variables had a significant effect on the outcome measures, and thus could be disregarded in further analyses. An overview of correlations between the independent and dependent variables is provided in Table 3.2.

Managerial role (dummy-coded, sales = -1, operations = 1) was not significantly related to forecasts or production quantities, but the negative direction of the relationship is as expected. Agent type (dummy-coded, cooperative = -1, competitive = 1) was negatively related to SVO. SVO was negatively related to the forecast in phase 1, indicating that a higher (prosocial) SVO is related to lower forecasts. Forecasts and production quantities were positively correlated across both phases.

Table 3.2: Descriptives and correlations

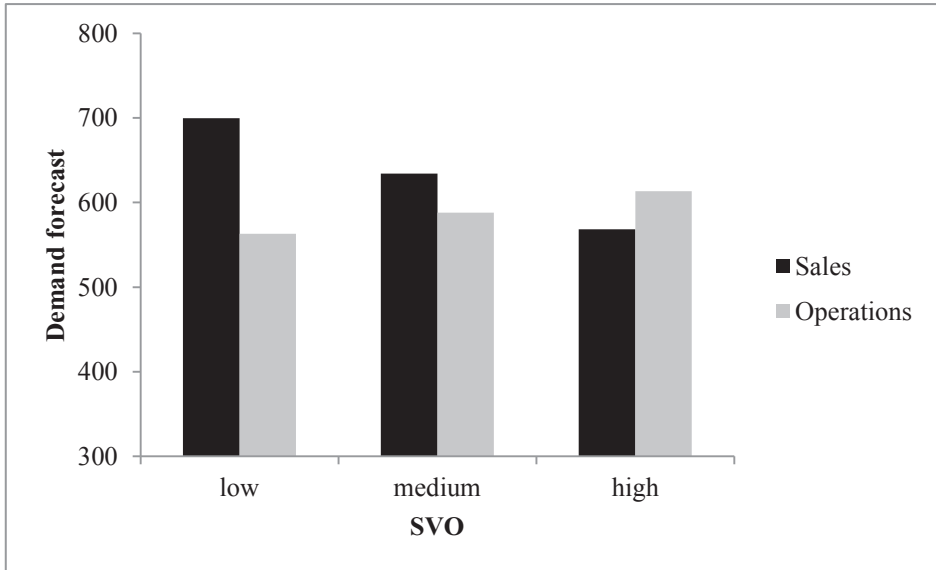
	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7
1 Managerial role	-.12	1.00	-						
2 Agent type	.00	1.00	-.08	-					
3 SVO	23.36	12.67	.04	-.22*	-				
4 Forecast 1	527.30	152.53	.03	.12	-.20*	-			
5 Forecast 2	615.62	222.92	-.11	-.12	-.11	.34**	-		
6 Production quantity 1	487.89	140.78	.10	.06	-.04	.49**	.48**	-	
7 Production quantity 2.1	599.70	231.92	-.13	-.09	-.01	.20*	.91**	.62**	-
8 Production quantity 2.4	612.40	225.88	-.03	-.06	.02	.26**	.80**	.66**	.92**

Note: * $p < .05$; ** $p < .01$, two-tailed.

Forecasting behavior. In the first phase, we did not find the predicted main effect of managerial role on forecast, $\beta = -44.75$, $t(100) = -0.71$, *ns.*, and communicated production quantities, $\beta = 53.02$, $t(100) = 0.90$, *ns.* Participants in the sales and operations role condition on average did not differ in their forecasting behavior. Analyses also did not reveal the predicted interaction effect of managerial role and SVO on forecasts, $\beta = 2.43$, $t(100) = 1.04$, *ns.* or production quantities, $\beta = -1.07$, $t(100) = -0.48$, *ns.* We did, however, find a significant main effect of SVO on forecasts, $\beta = -2.39$, $t(100) = -2.03$, $p < .05$, 95% CI = [-4.72; -0.06], which showed that participants high on SVO gave lower forecasts than participants low on SVO.

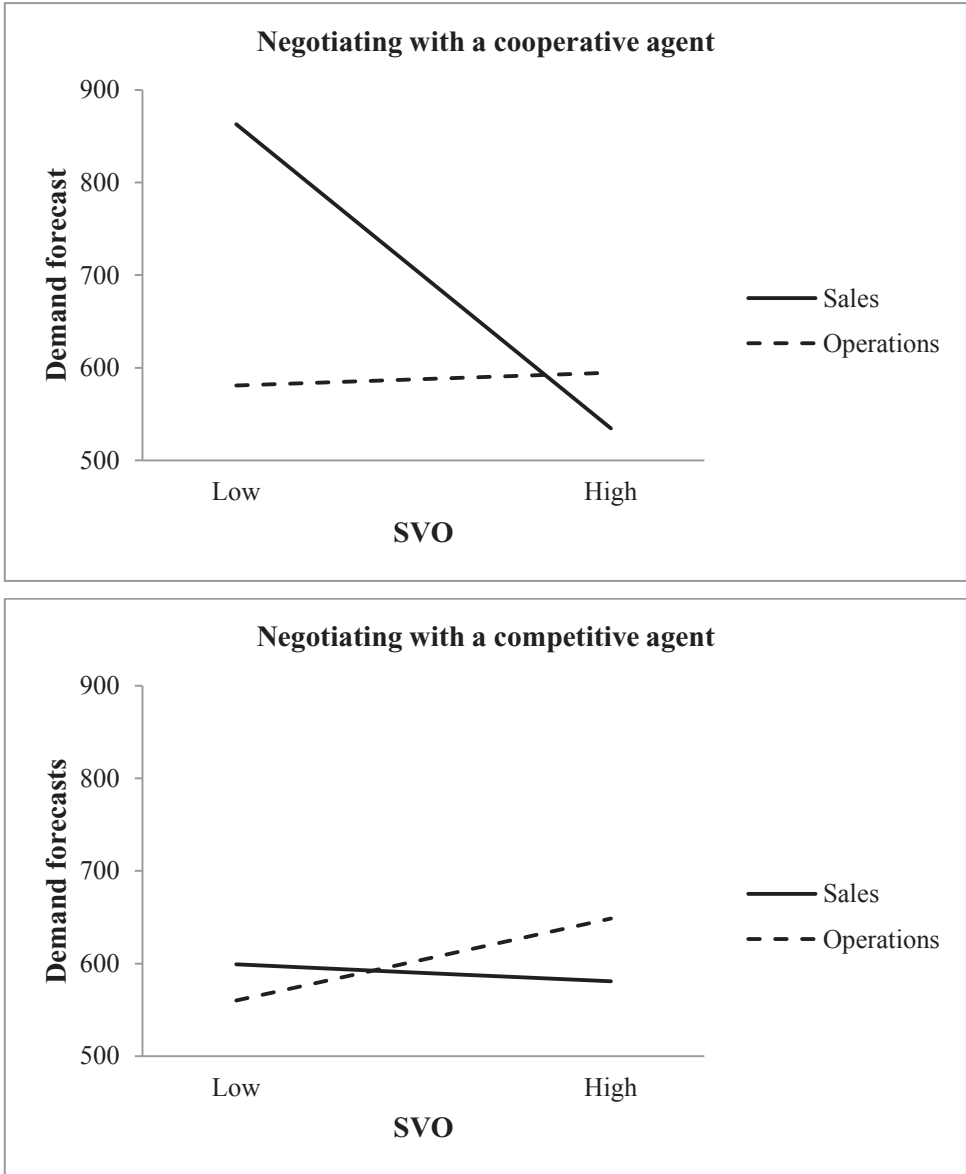
In the second phase, managerial role significantly affected the forecasts, $\beta = -255.41$, $t(96) = -2.71$, $p < .01$, 95% CI = [-442.51, -68.31] and production quantities ($Q2.1$), $\beta = -200.13$, $t(96) = -2.01$, $p < .05$, 95% CI = [-398.25, -2.01]. As predicted, participants in the operations role condition on average gave lower forecasts and communicated lower production quantities than those in the sales condition. Analyses also revealed the expected interaction effect of managerial role and SVO on forecasts, $\beta = 8.87$, $t(96) = 2.53$, $p < .05$, 95% CI = [1.92, 15.81] as shown in Figure 3.3. In line with expectations, participants low on SVO enacted their managerial role in a more biased way than those high on SVO. We found a trend towards the same pattern for communicated initial production quantities, $\beta = 6.02$, $t(96) = 1.63$, $p = .11$, 95% CI = [-1.33, 13.38]. Thus, while Hypotheses 1 and 2 had to be formally rejected for the first phase, they were confirmed for the second phase.

Figure 3.3: Average forecasts for managerial roles depending on SVO



Negotiation behavior. Hypothesis 3 predicted that forecasting behavior during the negotiation phase would depend on the joint interaction of managerial role, agent type and SVO. We did not find this overall three-way interaction effect on forecasts, $\beta = -9.29$, $t(96) = -1.33$, *ns.*, or production quantities, $\beta = -8.72$, $t(96) = -1.18$, *ns.* But analysis of the decomposed interaction terms made clear that the conditional effect of the managerial role–SVO interaction on forecasts existed for cooperative agents, $\beta = 13.51$, $t(96) = 2.51$, $p < .05$, 95% CI = [2.82, 24.20], but not for competitive agents, $\beta = 4.22$, $t(96) = .95$, *ns.* Participants in the sales role and low on SVO entered higher forecasts when playing against a cooperative agent than when playing against a competitive agent, see Figure 3.4.

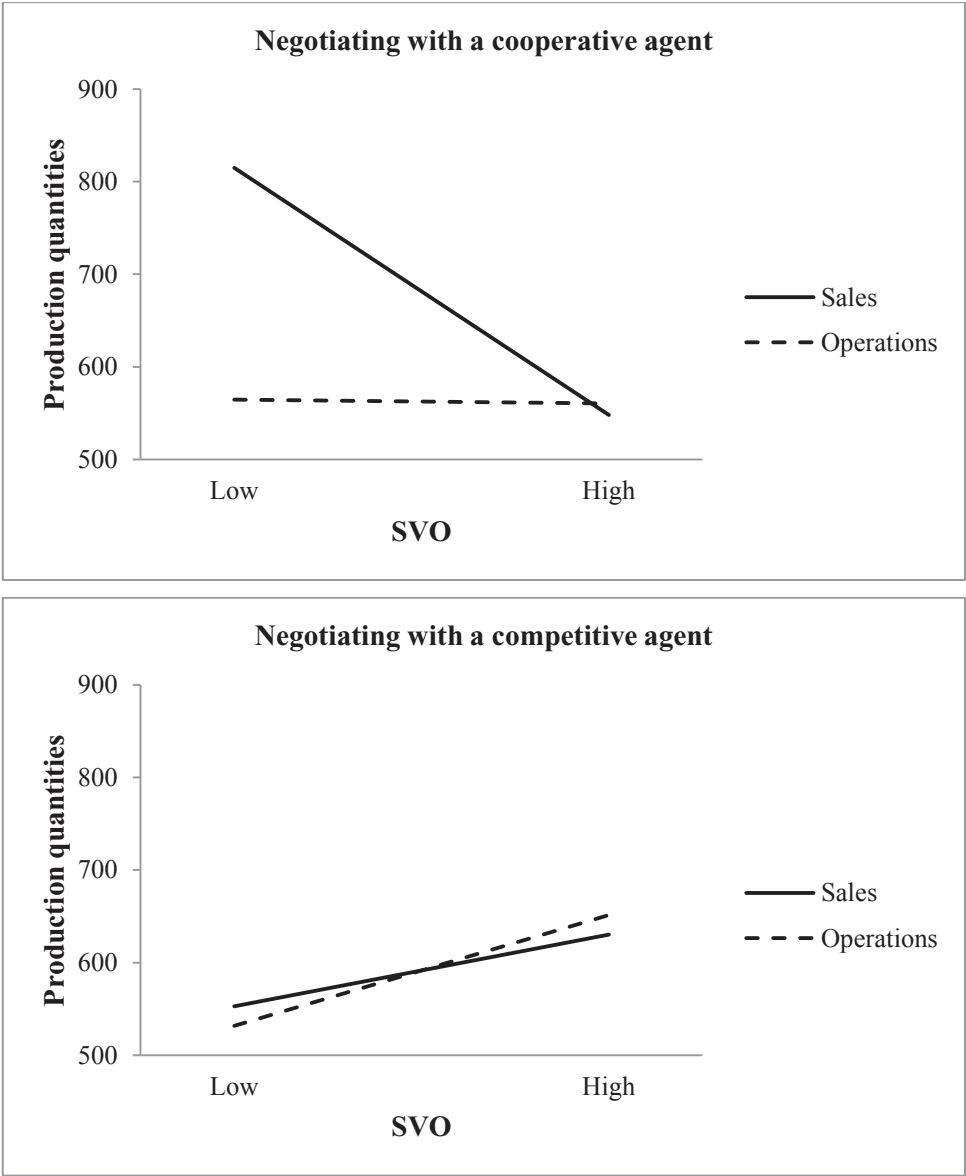
Figure 3.4: Demand forecast under different agent types in the negotiation



Albeit only marginal, the conditional effect of the role–SVO interaction on production quantities also existed for cooperative agents, $\beta = 10.38$, $t(96) = 1.82$, $p = .72$., 95% CI = [0.9363, 21.6977], but not for competitive agents, $\beta = 1.66$, $t(96) = .35$, *ns*.

Again, participants in the sales role and low on SVO entered higher production quantities when playing against a cooperative agent than when playing against a competitive agent, see Figure 3.5.

Figure 3.5: Production quantities under different agent types in the negotiation



Our predictions thus hold true for participants in the sales role condition especially in the face of a cooperative, but not a competitive, agent.

Forecast adjustment and concessions. To further our understanding of the forecasting and negotiation behavior of participants, we ran additional analyses at the level of forecast adjustment and concessions. A comparison between participants in the sales condition ($M = -1.12$; $SD = 4.43$) and participants in the operations condition ($M = -0.96$; $SD = 4.88$) in the first phase revealed no significant differences between the groups, $t(102) = -.18$, *ns*. However, in the negotiation phase, participants in the sales condition inflated their private forecasts ($M = 1.16$; $SD = 5.80$), whereas participants in the operations condition deflated their private forecasts ($M = -1.43$; $SD = 5.08$) when communicating the production quantity, $t(102) = 2.4$, $p < .05$. This is in line with their functional incentives. We also found a significant effect of managerial role in the negotiation phase on concession scores indicating that participants in the sales condition conceded downwards ($M = 2.50$; $SD = 5.74$), whereas participants in the operations condition conceded upwards ($M = -5.98$; $SD = 4.73$), $t(102) = 8.26$, $p < .01$.

3.5 Discussion and Conclusion

The lack of integration of sales and operations is an important shortcoming in judgmental forecasts, potentially undermining their accuracy. Using insights from research on negotiation (De Dreu & van Lange, 1995; De Dreu, 2010; Parks et al., 2013) and social dilemmas (Dawes & Messick, 2000; Van Lange, Joireman, Parks, & Van Dijk, 2013), we predicted that departmental affiliation within a company shapes a forecaster's perception about forecast negotiations. Results showed that departmental affiliation indeed influenced forecasting behavior in such a way that people with an operations role on average gave lower forecasts than those with a sales role. Furthermore, results made clear that this effect was moderated by people's social value orientation (SVO). First, forecasts were more extreme, in line with functional incentives when people were low (versus high) on SVO. Second, SVO steered the extent to which people's forecasting behavior and communicated production quantities was influenced by their departmental – most notably sales – affiliation, and the way they interacted with a cooperative or competitive negotiation counterpart.

Scientific relevance. From a scientific perspective, this research follows the call for more research of human behavior in operating environments (Bendoly, Donohue, & Schultz, 2006; Gino & Pisano, 2008) as it focuses on behavioral factors that influence forecast generation in organizations. We aim to make three important contributions. First of all, literature on forecasting usually focuses on the suitability and advantages of various forecasting techniques (a notable exception is Moritz, Siemsen, & Kremer, 2014). Moreover, despite the fact that most forecasting processes in organizations are based on interdepartmental cooperation, most behavioral research on forecasting has focused on either individual forecasters (Lawrence, Goodwin, O'Connor, & Önkal, 2006) or groups with undifferentiated roles (e.g. Ang & O'Connor, 1991). Our results relate to the growing literature on the role of managerial frames in forecasting (Kuo & Liang, 2004; Oliva & Watson, 2009; Önkal et al., 2011). We indeed demonstrate departmental biases in both the forecasts as well as communicated production quantities.

Second, combining insights from forecasting as well as social psychology literature, this study focuses on individual differences to define de-biasing strategies. Such de-biasing strategies require an understanding of the underlying psychological processes (Gigerenzer & Gaissmaier, 2011; Katsikopoulos & Gigerenzer, 2013) that lead sales and operations manager to over- or under-forecast respectively. By conceptualizing the interdepartmental forecasting process as a social dilemma, our study suggests that such intentional biases rooted in functional differentiation are less for individuals with a prosocial orientation. This is in line with a general stream of negotiation research that has shown that prosocial individuals exhibit more cooperation than proself individuals (Beersma & De Dreu, 2002; De Cremer & Van Lange, 2001; De Dreu & Van Lange, 1995). As such our study also offers a new managerial decision-making domain to explore motivational solutions to social dilemmas that primarily have been researched within the context of experimental games such as the prisoner's dilemma, the public goods dilemma or the tragedy of the commons (Balliet, 2010).

Finally, by taking motivational orientation of decision-makers into account to examine how forecast accuracy can be improved, our study of motivation in an operations management context also extends the scope of existing research in behavioral operations that mainly revolves around identifying decision-making biases in operations (Bendoly et

al., 2010). Albeit important heuristics and biases are not the only factors that affect choices and decisions, but also motivation or the lack thereof.

Practical relevance. This study touches upon a real-world forecasting problem, and that is the policy making function of forecasts in organizations (Wright & Rowe, 2011). Forecasts often serve particular purposes, for example, to justify promotion campaigns of the Marketing Department. Managerial pressure also often influences forecasts (Syntetos et al., 2009). Our study demonstrates – in a laboratory setting that was sufficient to motivate such purposive forecasting – that forecasts are rarely neutral and should be interpreted with care because forecasters are influenced by their departmental roles. It seems as if the departmental role offers a particular frame with which forecasters interpret information and make decisions. Furthermore, our results suggest that such deliberately biased forecasting behavior in forecast negotiations is not only a result of a forecaster’s departmental role, but also one’s individual disposition towards cooperation or conflict. From a managerial perspective, it means that it is not enough to understand the different goals and incentive structures that exist in organizations, but it is necessary to consider individual differences in motivational orientation of people that may impede or advance integrated solutions during interdepartmental negotiations. It is important to understand the social motives of members from different departments that need to cooperate in an interdepartmental negotiation process to generate forecasts. Especially, if organizational structures and processes cannot be modified in such a way that they reduce the inherent conflicts of interdepartmental negotiation, managerial interventions should aim at selection of employees in such a way that their personalities and behaviors ‘fit’ strategically communicated negotiation outcomes, and to establish a match between individual as well as common (organizational) interests. In other words, there is a need to manage the social value orientations of employees. Our research proposes a way forward. Framing interdepartmental forecast negotiations as cooperative, encouraging discussions between departments to understand the impact of individual decisions on others as well as allowing time for negotiation to converge opinions could all bridge the gap that organizational differentiation creates.

Limitations and future research. The present research raises several questions that merit attention and future research. In our study we found that social value orientation

is an important factor in judgmental forecasting, the adjustment of forecasts and negotiation between Sales and Operations Departments to determine a consensus forecast. However, with the present design we were unable to explain why this was the case. Interestingly, Nauta, De Dreu and Van der Vaart (2002) suggested that a high (prosocial) value orientation is related to the concern for goals of another department. Another possible explanation could be that social value orientation affects the conflict handling and negotiation strategy of the interdependent parties. De Dreu and Van Lange (1995) showed that people high on social value orientation cooperate more than people low on social value orientation, and gave more concessions during a negotiation. This seems to suggest that inclusion of self-, opponent- or observer-rated conflict management strategies (De Dreu, Evers, Beersma, Kluwer, & Nauta, 2001) may be worth considering. The investigation of potential mediators such as departmental goal concern or conflict handling style could therefore be a fruitful avenue for future research. Third, in our experiment, we measured social value orientation as a dispositional factor, whereas it can also be situationally induced (De Dreu et al., 2000). The latter approach would allow us to not only manipulate departmental goals, but also social motives so as to mimic the conflict of the social dilemma of negotiated forecasts. Finally, it should be noted that our conclusions apply to a dyadic situation. We chose to include sales and operations as potentially the most contrasting organizational units in the forecasting process in terms of goals, incentives and planning horizons. However, in practice, the forecasting process may also include other departments such as finance and marketing. Thus, future research could incorporate not only more managerial roles, but also switch from human-agent computer interaction to face-to-face group discussions in which several issues at varying degrees of priority for different departments can be negotiated about.

Conclusion. Our study advances the work on behavioral forecasting by integrating social psychological research with research on forecasting to disentangle the complex nature of cooperation in social dilemmas in the context of the forecasting process. Results make clear that the departmental affiliation and social value orientation shape a forecaster's perception of forecast negotiations and influence the accuracy of demand forecasts.

4 Managerial role, organizational incentives and goal concerns in interdepartmental forecast negotiations

Incompatible departmental goals potentially undermine the accuracy of demand forecasts in collaborative forecasting processes. Using insights from research on forecast collaboration and negotiation, we posit that departmental affiliation within a company shapes forecasting behavior in inter-departmental forecast negotiations commonly found in companies. Experimental results confirmed our prediction that managerial role and incentives jointly affect the concern for particular goals which in turn influence forecasting behavior during negotiations. The study suggests that the influence of departmental affiliation on forecast accuracy can be explained by self-concern and attenuated by organizational incentives.

4.1 Introduction

Matching demand and supply is paramount for many firms because a mismatch is costly and affects a company's short- and long-term profitability (Hendricks & Singhal, 2009). If demand is underestimated, inventory levels may be too low to fulfill customer orders, which could translate into damaged customer relationships and lost sales. If demand is overestimated, inventory may build up causing inventory holding costs and products possibly become obsolete before they can be sold. In order to align demand and supply, coordination between different functional departments within firms is important to accurately forecast and fulfill customer demand. In many organizations, forecasting processes usually include different departments, such as marketing, sales, production and operations (Lawrence, O'Connor, & Edmundson, 2000). However, achieving coordination among the different parties is nontrivial due to diverging interests, goals and incentives that shape organizational behavior. In an interdepartmental forecasting process, different departments may set forecasts in line with their incentives in order to achieve specific (departmental) objectives, thereby jeopardizing the accuracy of the forecast. The case study by Oliva and Watson (2011) illustrates how functional biases can affect forecasting performance.

The literature on forecast collaboration *within* firms has especially focused on ways to engage and motivate the sales force (Chen, 2005; Gonik, 1978; Lal & Staelin, 1986; McCarthy Byrne, Moon, & Mentzer, 2011), and the marketing-manufacturing interface (Celikbas, George Shanthikumar, & Swaminathan, 1999; Li & Atkins, 2002; Porteus & Whang, 1991). The literature on forecast sharing *between* firms has concentrated on identifying contract designs to incentivize retailers and manufacturers to share demand forecasts and information credibly (Cachon & Lariviere, 2001; Özer & Wei, 2006). In practice, organizations use incentive schemes to reduce such dysfunctional forecasting behavior by, for example, including forecast accuracy in performance evaluations.

When departmental goals are incompatible, members of different departments face the dilemma of choosing between their own departmental goal and an overall organizational goal (Nauta, Dreu, & Vaart, 2002). Applying this insight to the context of forecast collaboration within firms, forecasters face the dilemma of serving their own departmental goal, for example reaching a certain sales quota or forecasting accurately, as accurate forecasts may benefit the overall organization but put the achievement of departmental objectives at risk. The well-established dual concern model (Pruitt & Carnevale, 1993; Rubin, Pruitt, & Kim, 1994) distinguishes between a concern for one's own and others' goals. A key finding of negotiation research is that negotiators are more likely to engage in problem solving behavior when they are concerned about their own as well as their opposing negotiator's outcome (De Dreu, Weingart, & Kwon, 2000).

The present research applies these insights to negotiated demand forecasts and focuses on the extent to which departmental affiliation within a company shapes forecast and negotiation behavior in forecast meetings. Given the departmental affiliation, we explore the related issue whether the extent to which a forecaster produces accurate forecasts and shares credible information depends on the type of incentive – that is, a departmental incentive to pursue functional goals or a collective incentive to pursue forecast accuracy. In addition, we posit that goal concerns affect forecasting and negotiation behavior in the collaborative forecasting process.

We conducted a laboratory study where participants make a private forecast decision and communicate a production quantity to a negotiation partner over sequential periods after observing historic demand. This allows us to disentangle the influence of

managerial role and incentives on forecast and negotiation behavior. Moreover, we explore whether managerial roles and incentives jointly explain why people bias their forecast and distort their production quantity. An explanation for such behavior, that we examine, is the concern for either departmental or collective goals.

4.2 Theoretical background

The phenomenon of demand forecast distortion has been studied extensively in the literature on supply chain information sharing, usually focusing on inter-organizational settings with dyads of a retailer and a supplier or manufacturer (e.g. Aviv, 2001; Mishra, Raghunathan, & Yue, 2009) who have conflicting interests that impact their forecast sharing behaviors. Similarly, in organizational forecasting, each member represents a different department subject to potentially diverging incentives and motivations. Such differentiation generates conflicts over differing expectations, preferences, and priorities with respect to how the matching of demand and supply should be accomplished (Shapiro, 1977). Importantly, an emerging research in operations management now indicates that the forecasting process is influenced by a forecaster's departmental role (Kuo & Liang, 2004; Önkal, Lawrence, & Zeynep Sayim, 2011). In their case study, Oliva and Watson (2011) describe a consensus forecasting process that includes various departments and that illustrates how functional biases could affect forecasting performance. Another study examining the effect of organizational roles on forecasting showed that differential organizational roles, that is, being part of a Marketing or Production Department, distorts judgmental forecasts in line with organizational incentive structures (Önkal et al., 2011). The same conclusion can be drawn from a study by Kuo and Liang (2004) where forecasters differed in their judgment even when they receive the same information. Within companies, forecasts may be consistently biased, if incentives of different organizational departments encourage over- or under-forecasting to reach departmental targets (Lawrence et al., 2000). This is especially true when forecasts are connected to targets and functional performance. A production manager who aims at keeping inventory levels low, may provide lower forecasts, while a product manager who is concerned with sufficient product availability, may set forecasts high to avoid lost sales.

The literature on supply chain information sharing has examined ways to mitigate the problem of forecast manipulations in inter-organizational settings, such as repeated interaction (Ren, Cohen, Ho, & Terwiesch, 2010) or contract design to align incentives (e.g. Cachon & Lariviere, 2001; Özer & Wei, 2006). Focusing on inter-individual differences of decision-makers, Özer, Zheng and Chen (2011) examine the role of trust and trustworthiness in fostering credible forecast information sharing, and thereby took a behavioral perspective on forecasting. Similarly, differential goals and interdependence affect an individual's motivations and decisions in various operations management settings (Bendoly, Croson, Goncalves, & Schultz, 2010).

Employees in organizations usually aim at the goals of their own department and little, if at all, at goals of another department. This has been termed *narrow role orientation* (Parker, Wall, & Jackson, 1997). If the concern for particular goals is indeed the main process through which functional differentiation affects behavior in inter-departmental negotiations (Nauta et al., 2002), it seems sensible to focus on incentives that stimulate either the pursuit of individual or collective goals in the forecasting process. In fact, incentives as opposed to contracts in inter-organizational settings may positively affect forecast accuracy, if they emphasize accuracy as a goal (Önkal et al., 2011). On the other hand, if incentives differ, the effect of a forecaster's departmental role can be amplified as a study by Yaniv (2011) showed. In this study, homogenous groups with the same incentive did not reveal a framing effect of different roles, whereas heterogeneous groups with differing incentives showed a strong framing effect.

We expect sales people to be concerned with their departmental goals of selling and having sufficient products in stock to minimize lost sales, especially when incentives highlight the pursuit of departmental goals rather than collective company-wide goals. Operations people are likely to be concerned with their departmental goal of keeping inventory levels low to avoid obsolescence costs, if products cannot be sold. On the contrary, incentives that highlight the importance of forecast accuracy to improve company profits represent a collective goal. While departmental incentives are likely to reinforce the concern with particular functional goals, company incentives are likely to mitigate the negative effect of functional differentiation on goal concern and may lead

people to be more concerned with forecast accuracy instead of departmental goals. We thus predict the following:

Hypothesis 1a: Incentives moderate the relationship between managerial role and goal concern for lost sales: sales managers are more concerned with minimizing lost sales when following departmental incentives instead of company incentives than operations managers.

Hypothesis 1b: Incentives moderate the relationship between managerial role and goal concern for obsolesces: operations managers are more concerned with minimizing obsolesces when following departmental incentives instead of company incentives than sales managers.

Hypothesis 1c: Incentives moderate the relationship between managerial role and goal concern for forecast accuracy: both sales and operations managers are more concerned with maximizing forecast accuracy when following company incentives instead of departmental incentives.

Although departments determine the monthly forecast mostly independently, the task of arriving at a consensus forecast that determines the production quantity is a collaborative process. This often involves negotiations and information sharing prior to the forecast meeting. Being a member or representative of a specific (organizational) department may not only have an impact on someone's goal concern, but also on forecasting behavior and the extent to which information is credibly shared – that is whether the communicated forecast prior to the planning meeting is equal to the private forecast. Importantly, the concern for one's own or other goals are “motivating desires to reach certain outcomes” (Janssen & Van de Vliert, 1996, p.102) and is not a goal in itself. Hence, goal concern for lost sales and goal concern for obsolesces explain why sales and operations with a departmental incentive bias their forecasts and distort production quantities in line with their objectives. Goal concern for forecast accuracy by contrast explains why the same departments with a forecast accuracy incentive try to more accurately predict demand and credibly share their production quantity. We expect that

organizational roles impact both, the (private) forecasts and the extent to which these forecasts are distorted in pre-meeting communications. We thus predict the following:

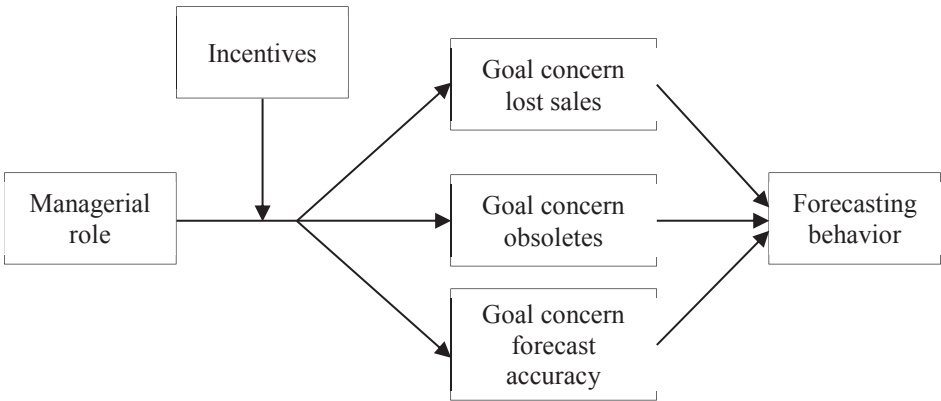
Hypothesis 2a: Goal concern for lost sales mediates the moderating effect of incentives on the relationship of managerial role with forecasts, production quantities and forecast inflation.

Hypothesis 2b: Goal concern for obsoletes mediates the moderating effect of incentives on the relationship of managerial role with forecasts, production quantities and forecast inflation.

Hypothesis 2c: Goal concern for forecast accuracy mediates the moderating effect of incentives on the relationship of managerial role with forecasts, production quantities and forecast inflation.

Figure 4.1 graphically presents the model for this study. In sum, we propose that incentives moderate the role–forecasting behavior relationship and that this moderating effect is mediated by the goal concern for lost sales, goal concern for obsoletes and goal concern for forecast accuracy. The hypotheses were put to the test in a laboratory experiment, which gave us full control over our experimental conditions and the experimental task, and allowed us to measure participant’s forecasting behavior with a relatively high degree of objectivity.

Figure 4.1: Proposed model experiment 2



4.3 Method

In this study, we build on and adapt the experimental design that we used in an earlier study on behavioral forecasting (Protzner, Pennings, Rook, & Van Dalen, 2015). While the first study explored the effect of managerial role and social value orientation in negotiated demand forecasts, we use an explicit differential incentive scheme in this study to explore whether the effect of managerial roles on forecasting behavior is reinforced or mitigated by incentives. Organizational incentives can either emphasize cooperative versus competitive goals and may elicit cooperation or competition among different departments in the forecasting process. Moreover, we explore whether managerial roles and incentives jointly lead people to be concerned with different goals which in turn affect forecasting behavior and possibly forecast manipulations.

Participants and Design

Participants were randomly assigned to the conditions of a 2 (managerial role: sales, operations) X 2 (incentive: department, company) factorial design. The sample consisted of 245 participants (147 men, 98 women, M age = 22.49 years, SD = 5.61). The majority (210 participants) was from a Dutch university who received course credits for participation. The remaining 35 participants were professionals from a Dutch company. The experiment was conducted at the behavioral laboratory of the university.

Materials and Procedure

At the beginning of the experiment, participants completed a training phase in which they could familiarize themselves with the forecasting task. After the training phase, participants received instructions for the experimental task containing the role manipulations, together with background information about the company, a producer of fresh juice for which they presumably worked as a demand planner. Participants were instructed to forecast demand for the product for the coming month (one month equaled one period) and provide input (i.e. a production quantity) to a planning meeting with another demand planner in each period. The experimental task consisted of two separate phases in which the participant was provided with 18 periods of historic demand data. We

used the same demand series as in our first behavioral forecasting study (Protzner et al., 2015).

In the first phase, participants had to provide: (1) a private, not shared forecast of the demand, and (2) a separate production quantity in each period. The latter was used as an input for the planning meeting, and shared with the other demand planner. After each period, participants could see the outcome of the planning meeting – i.e. the production quantity calculated as the average of their own and the other demand planner’s input. This average determined the final production quantity. The participant could also observe actual demand after decision making and reception of feedback about forecast accuracy, lost sales, obsolete units, company profit and individual performance score. After the first phase, participants were informed about a change in the company’s policy regarding forecast generation – a three-round negotiation process would be introduced into the planning meeting. After submitting their production quantity, participants could see the other demand planner’s production quantity and decide whether or not to adjust their own input.

The interdepartmental forecast negotiations were conducted electronically, and participants played against a pre-programmed computer agent. Participants with a sales manager role encountered an operations manager in the meeting and participants with an operations manager role encountered a sales manager in the meeting. Upon completion, participants were directed to an online post-questionnaire including manipulation checks. Participants were debriefed at the end of the experiment.

Manipulation of managerial role. Participants received instructions that described their role as either sales or operations manager as follows:

- (1) You are an operations manager. Your job is about getting work done quickly, efficiently, without error, and at low cost. Minimizing costs is a key responsibility of this position. Unsold juices are obsolete at the end of a period, as they are no longer fresh. A high level of obsolesces means that you will have to destroy products that you produced and for which you employed resources. As a result you will have incurred obsolescence costs, namely 1€ production cost for every unsold bottle of orange/mango juice. Keep that in mind when providing input for the planning meeting!

- (2) You are a sales manager. Maximizing customer service levels and increasing sales are key responsibilities of this position. Sales involves meeting the sales targets of the organization through developing sales plans that identify the sales possibilities and future market conditions. Sales are, of course, a launch pad for profit. If there are not enough products available, *Sunrise* incurs cost of lost sales and profits are foregone. Lost sales cost you 1€ for every bottle of unfulfilled demand. Keep that in mind when providing input for the planning meeting!

Manipulation of incentive. Participants received instructions that described their incentive either as a departmental or company incentive, and aimed at triggering the adoption of goal-driven behavior. The departmental incentives were chosen based on the distinct costs each function incurs from a mismatch between demand and supply (Fisher, 1997). The respective instructions for the operations and sales manager in the departmental incentive condition were as follows:

- (1) As in most companies, your performance as an operations manager is evaluated based on how well you achieve the goals of your operations function. That means minimizing the number of obsolete products and the associated obsolescence costs every month.
- (2) As in most companies, your performance as a sales manager is evaluated based on how well you achieve the goals of your sales function. That means minimizing the number of lost sales and the associated costs of lost sales every month.

Instructions for the operations and sales manager in the company incentive condition only differed in the ascribed role:

- (3) *Sunrise* is naturally keen to forecast as accurately as possible in order to reduce the potential costs. To achieve that goal, the performance of every manager is evaluated based on how accurate demand is forecasted. Your performance as an operations manager/sales manager is evaluated based on the accuracy of the consensus forecast every month. Forecast accuracy is measured as the mean absolute percentage error (Mape). This error percentage should be as low as possible.

Dependent measures

Goal concerns. To measure goal concern, we used the item developed by Nauta et al. (2002) but adapted the goals to fit the forecasting context (minimizing lost sales, minimizing obsolete units, maximizing forecast accuracy). Participants were asked the following question: “For each of the goals, can you indicate the degree to which you actually aimed at it during the experiment? This may be, for example, because the goal is part of your job, because you are rewarded for achieving it, or because you believe the goal to be important for another reason.”

Forecasts. We recorded participants’ forecasts for each period and phase, including the training phase. In order to compare groups, we averaged an individual’s forecasts for each phase, where for phase 1 *FC1* denotes the average forecast of round 1 to 10 and for phase 2, *FC2* denotes the average forecast of round 11 to 20.

Production quantities. We recorded participants’ production quantities Q for each period and phase. As participants entered only one production quantity as meeting input in phase 1, we proceeded with calculating the participant’s average production quantity $Q1$ for phase 1 as described above. For phase 2, we averaged an individual’s initial production quantities ($Q2.1$) that were entered at the beginning of the negotiation. Similarly, we also averaged the final production quantities that were entered at the end of the negotiation ($Q2.4$).

Forecast inflation. For each period and phase, we recorded the deviation between the private forecast and the communicated production quantity that indicated to what extent participants inflated or deflated their private forecasts. A score of zero would indicate that both numbers are the same. A positive (versus negative) value would indicate forecast inflation (versus deflation) as the production quantity in this case would be higher (versus lower) than the forecast.

Concessions. Finally, for the negotiation phase, we recorded concession behavior from the first to the final negotiation cycle in each period, indicating whether participants moved towards or away from their negotiation counterpart (i.e., the agent). This was calculated as the absolute deviation between the initial and final production quantity.

4.4 Results

Manipulation checks

Our manipulation of managerial roles was intended to affect participant's forecasting behavior. To check whether our manipulation had been successful, we asked participants about their role in the forecasting committee. The two items were: "What was your specific role in the forecasting meeting?" and "According to the instructions, which manager were you?" A *t*-test revealed significant differences in role understanding for sales ($M = 1.08$) and operations ($M = 1.93$), $t(243) = -25.49, p < .001$. Hence, participants in the sales condition understood their role as sales managers whereas participants in the operations condition understood their role as operations managers. Our manipulation of incentive was intended to make participants follow a departmental or company-wide goal. To check whether participants had understood their incentive, we asked participants how their performance in the experiment was evaluated. A *t*-test revealed significant differences in incentive understanding for departmental incentive ($M = 1.40$) and company incentive ($M = 1.79$), $t(243) = -6.71, p < .001$. This indicated that both manipulations indeed triggered managerial role and incentives, respectively.

Training phase

In the training phase, there were no significant differences in participants' forecasts, $F(1, 244) = .004, ns.$, and performance as indicated by the mean average percentage error (Mape), $F(1, 244) = 1.25, ns.$ between the four experimental conditions. This was expected as the role and incentive manipulations were only administered after the training phase. Thus, without specific role and incentive instructions participants forecasted and performed equally.

Hypotheses test results

An overview of the means, standard deviations and correlations among the study variables is provided in Table 4.1. Managerial role (dummy-coded, sales = -1, operations = 1) was not related to forecast, production quantity or forecast inflation in phase 1 while it was negatively related to production quantity and forecast inflation as well as the deviation between initial and final production quantity in phase 2. Managerial role was also

negatively related to goal concern for lost sales and positively related to goal concern for obsolesces. Incentive type (dummy-coded, departmental = -1, company-wide = 1) was positively related to goal concern for forecast accuracy. Goal concern for lost sales was positively related to production quantity in phase 1 and to forecast, production quantity and forecast inflation in phase 2. Goal concern for obsolesces was negatively associated with production quantity in phase 1 and 2, and with forecast inflation in phase 2. Goal concern for forecast accuracy was positively related to production quantity and forecast inflation in phase 2.

The descriptive statistics resulting from the experimental conditions are given in Table 4.2. As can be seen, participants across all four conditions on average do not differ in their training forecasts. While the participants in the company incentive condition continue to give almost the same forecast and production quantities independent of their sales or operations role, participants in the department condition on average differ in their forecast and production quantities, especially in phase 2.

Table 4.1: Descriptives and correlations

	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9	10	11
1 role	-0.3	1.00	-										
2 incentive	.00	1.00	.00	-									
3 GC LS	3.35	1.25	-.31**	.01	-								
4 GC OBS	3.42	1.21	.28**	-.08	.18**	-							
5 GC MAPE	4.27	.97	.03	.33**	-.02	-.03	-						
6 FCT	1234.14	72.24	-.02	-.07	.02	-.07	-.10	-					
7 FC 1	472.98	63.13	.00	-.05	.11	-.07	-.08	.28**	-				
8 FC 2	590.10	43.83	-.04	-.14*	.22**	-.08	.04	.19**	.36**	-			
9 Q 1	456.38	85.67	-.10	.07	.17**	-.13*	.06	.07	.61**	.24**	-		
10 Q 2.1	590.34	94.73	-.18**	.04	.26**	-.17**	.15*	.02	.16**	.57**	.30**	-	
11 Infl_1	-16.60	68.91	-.12	.13*	.11	-.10	.16*	-.18**	-.16*	-.03	.69**	.22**	-
12 Infl_2	.24	78.59	-.19**	.12	.19**	-.16*	.16*	-.08	.00	.13*	.23**	.89**	.28**

Note: * $p < .05$; ** $p < .01$, two-tailed

Table 4.2: Descriptives for experimental conditions

	Department incentive				Company incentive			
	Sales		Operations		Sales		Operations	
	<i>Mean</i>	<i>Std. Dev.</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Mean</i>	<i>Std. Dev.</i>	<i>Mean</i>	<i>Std. Dev.</i>
	<i>N</i> = 63		<i>N</i> = 60		<i>N</i> = 63		<i>N</i> = 59	
FC T	1240.20	69.48	1238.04	83.42	1230.68	73.38	1227.41	62.02
FC 1	478.90	68.00	472.67	65.88	467.46	41.26	472.85	74.29
FC 2	600.73	47.45	590.98	49.71	582.90	37.14	585.53	38.54
Q1	465.84	83.55	434.39	110.49	463.83	68.90	460.69	72.43
Q2.1	615.06	101.35	556.64	111.30	598.17	59.29	589.84	92.26
INFL 1	-13.06	69.28	-38.29	95.83	-3.63	58.89	-12.15	33.08
INFL2	14.33	90.66	-34.34	86.08	15.27	36.73	4.31	80.65

To test our hypotheses, we performed separate hierarchical regression analyses. In each regression, we entered the control variables gender, cohort, experience, and age in the first step. Managerial role and incentive type were entered as independent variables in step 2. In step 3, the interaction between managerial role and incentive type were also entered as predictors. Finally, goal concern for lost sales, goal concern for obsoletes, and goal concern for forecast accuracy were entered as mediators in step 4. Tables 4.3 and 4.4 summarize the results for phase 1 and phase 2, respectively.

Main effects of managerial role and incentive type. In both phases, the results of the regression analysis indicate that managerial role explains a significant amount of variance in goal concern for lost sales ($\Delta R^2 = .09$, $F(6,238) = 4.89$, $p < .01$) and goal concern for obsoletes ($\Delta R^2 = .08$, $F(6,238) = 4.51$, $p < .01$), exceeding the variance explained by the controls. Managerial role significantly predicted the extent to which participants were concerned with minimizing lost sales ($\beta = -.31$, $p < .01$) and minimizing obsoletes ($\beta = .28$, $p < .01$): participants with a sales role were more concerned with minimizing lost sales ($M = 3.72$, $SD = 1.12$) than participants with an operations role ($M = 2.96$, $SD = 1.27$) while participants with an operations role were more concerned with minimizing obsoletes ($M = 3.77$, $SD = 1.14$) than participants with a sales role ($M = 3.09$, $SD = 1.19$). Incentive type explained 14 percent of the variance in goal concern for forecast accuracy, significantly exceeding the variance explained by the controls ($\Delta R^2 = .12$, $F(6,238) = 6.18$, $p < .01$). Incentive type significantly predicted the extent to which participants were concerned with maximizing forecast accuracy ($\beta = .35$, $p < .01$): participants with a company incentive were more concerned with maximizing forecast accuracy ($M = 4.59$, $SD = .68$) than participants with a departmental incentive ($M = 3.94$, $SD = 1.11$).

Managerial role significantly predicted forecast inflation in phase 1 ($\beta = -.13$, $p < .05$) and phase 2 ($\beta = -.19$, $p < .01$) such that, for example for phase 2, participants with an operations role deflated their private forecasts ($M = -15.18$, $SD = 85.31$) while participants with a sales role inflated their forecasts ($M = 14.80$, $SD = 68.89$). In phase 2, managerial role also significantly predicted production quantity ($\beta = -.18$, $p < .05$) to such an extent that participants with an operations role gave lower production quantities ($M = 573.10$, $SD = 103.23$) than participants with a sales role ($M = 606.61$, $SD = 83.13$).

Table 4.3: Results of regression analysis - phase 1

Independent variables	Model 1: GC lost sales			Model 2: GC obsoletes			Model 3: GC maape			
	1	2	3	1	2	3	1	2	3	
Step 1: Control variables										
Gender	.05	.04	.03	-.05	-.04	-.04	-.06	-.06	-.06	-.06
Cohort	.12	.12	.11	.11	.11	.12	.14	.14 [†]	.14 [†]	.14 [†]
Experience	.05	.07	.07	.11	.08	.09	.03	.07	.07	.07
Age	-.12	-.10	-.10	-.03 [†]	-.04	-.05	-.13	-.17*	-.17*	-.17*
Step 2: Main effects										
Role		-.31**	-.31**		.28**	.28**		.03	.03	.03
Incentive		.02	-.02		-.07	-.07		.35**	.35**	.35**
Step 3: Interactions										
Role x Incentives			.10			-.13*				.02
Step 4: Mediators										
GC lost sales										
GC obsoletes										
GC maape										
R^2	.02	.11	.12	.02	.10	.12	.02	.14	.14	.14
ΔR^2	.02	.09**	.01	.02	.08**	.02*	.02	.12**	.12**	.00
F	1.01	4.89	4.58	1.37	4.51	4.57	.88	6.18	6.18	5.24

n = 245. Standardized regression coefficients are reported.

[†] $p < .10$

* $p < .05$

** $p < .01$

Table 4.3 continued

Independent variables	Model 4: forecast				Model 5: production quantity				Model 6: forecast inflation			
	1	2	3	4	1	2	3	4	1	2	3	4
Step 1: Control variables												
Gender	.001	.001	.001	-.01	-.05	-.06	-.06	-.07	-.07	-.07	-.08	-.07
Cohort	-.09	-.09	-.09	-.08	-.04	-.04	-.04	-.05	.04	.04	.04	.02
Experience	.06	.05	.05	.06	.07	.09	.08	.08	.04	.06	.06	.05
Age	-.04	-.03	-.03	-.04	-.02	-.02	-.02	.002	.01	.01	.01	.04
Step 2: Main effects												
Role		-.003	-.002	.07		-.11 [†]	-.11 [†]	-.01		-.13*	-.13*	-.08
Incentive		-.03	-.03	-.02		.08	.08	.06		.13*	.13*	.08
Step 3: Interactions												
Role x Incentives			.05	.02		.08	.08	.04		.06	.06	.04
Step 4: Mediators												
GC lost sales				.15*				.19**				.11
GC obsoletes				-.12				-.16*				-.09
GC mape				-.08				.04				.13 [†]
R^2	.02	.02	.02	.05	.01	.03	.03	.08	.01	.04	.05	.07
Δ												
R^2	.02	.00	.00	.03 [†]	.01	.02	.00	.04*	.01	.03*	.01	.02 [†]
F	.98	.69	.66	1.15	.60	1.14	1.21	1.89	.43	1.71	1.59	1.77

n = 245. Standardized regression coefficients are reported.

[†] $p < .10$

* $p < .05$

** $p < .01$

Table 4.4: Results of regression analysis - phase 2

Independent variables	Model 1: GC lost sales			Model 2: GC obsoletes			Model 3: GC maape			
	1	2	3	1	2	3	1	2	3	
Step 1: Control variables										
Gender	.05	.04	.03	-.05	-.04	-.04	-.06	-.06	-.06	-.06
Cohort	.12	.12	.11	.11	.11	.12	.14	.14 [†]	.14 [†]	.14 [†]
Experience	.05	.07	.07	.11	.08	.09	.03	.07	.07	.07
Age	-.12	-.10	-.10	-.03 [†]	-.04	-.05	-.13	-.17*	-.17*	-.17*
Step 2: Main effects										
Role		-.31**	-.31**		.28**	.28**		.03	.03	.03
Incentive		.02	-.02		-.07	-.07		.35**	.35**	.35**
Step 3: Interactions										
Role x Incentives			.10			-.13*				.02
Step 4: Mediators										
GC lost sales		.11	.12	.02	.10	.12	.02	.14	.14	.14
GC obsoletes	.02	.09**	.01	.02	.08**	.02*	.02	.12**	.12**	.00
GC maape	1.01	4.89	4.58	1.37	4.51	4.57	.88	6.18	6.18	5.24
R^2										
ΔR^2										
F										

n = 245. Standardized regression coefficients are reported.

[†] $p < .10$

* $p < .05$

** $p < .01$

Table 4.4 continued

Independent variables	Model 4: forecast				Model 5: production quantity				Model 6: forecast inflation			
	1	2	3	4	1	2	3	4	1	2	3	4
Step 1: Control variables												
Gender	.05	.05	.05	.04	-.01	-.01	-.02	-.02	-.03	-.04	-.05	-.05
Cohort	.09	.08	.08	.05	.07	.06	.06	.03	.03	.03	.03	.002
Experience	.01	-.01	-.01	-.02	-.04	-.03	-.03	-.04	-.05	-.03	-.03	-.04
Age	-.09	-.07	-.07	-.04	-.07	-.06	-.05	-.01	-.03	-.03	-.02	.01
Step 2: Main effects												
Role		-.04	-.04	.09	-.18*	-.18**	-.18**	-.04	-.19**	-.19**	-.19**	-.10
Incentive		-.13*	-.13*	-.18**	.04	-.04	-.04	-.03	.12†	.12†	.12†	-.06
Step 3: Interactions												
Role x Incentives			.07	.02		.13*		.08		.12†		.08
Step 4: Mediators												
GC lost sales				.27**				.28**				.19**
GC obsolete				-.16*				-.20**				-.15*
GC mape				.10				.16*				.14*
R^2	.01	.03	.03	.10	.004	.04	.05	.15	.004	.06	.07	.12
ΔR^2	.01	.02	.00	.07**	.004	.03*	.02*	.10**	.004	.05**	.02†	.05**
F	.53	1.12	1.12	2.70	.26	1.49	1.91	4.11	.26	2.29	2.52	3.23

n = 245. Standardized regression coefficients are reported.

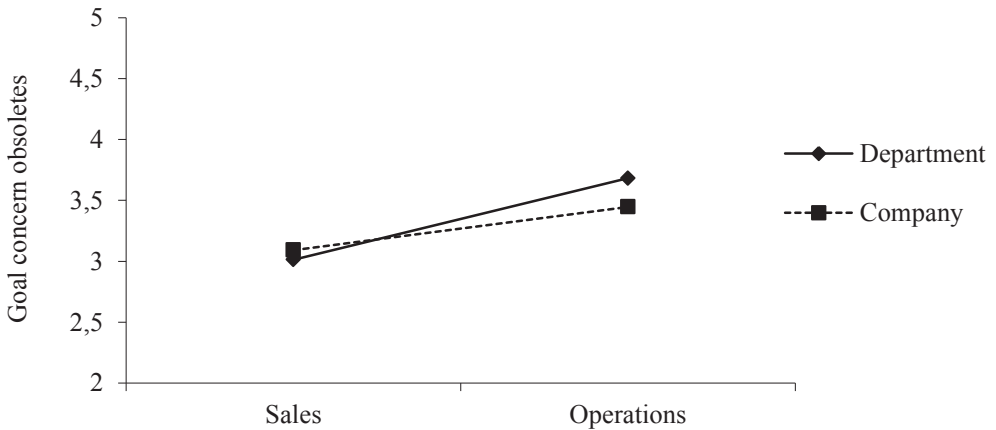
† $p < .10$

* $p < .05$

** $p < .01$

Interaction of managerial role and incentive type. The interaction of managerial role and incentive type only explained a significant amount of variance in goal concern for obsolesces, exceeding the variance explained by the control variables and the main effects ($\Delta R^2 = .02, p < .05$). There was no interaction of managerial role and incentive type for goal concern for lost sales ($\beta = .10, p = .11$) or goal concern for forecast accuracy ($\beta = .02, p = .79$) as posited in Hypotheses 1a and 1c. Simple slope tests (Aiken & West, 1991) showed that participants with an operations role had a higher concern for minimizing obsolesces when having a departmental incentive ($\beta = .49, t = 4.69, p < .01$) rather than a company incentive ($\beta = .18, t = 1.68, p < .1$). This result, illustrated in Figure 4.2, lends support to Hypothesis 1b.

Figure 4.2: Incentive as a moderator of the relationship between role and goal concern obsolesces



In phase 2, the interaction of managerial role and incentive type explained a significant amount of variance in production quantity ($\Delta R^2 = .02, p < .05$) and (albeit only marginally) forecast inflation ($\Delta R^2 = .02, p < .1$), exceeding the variance explained by the control variables and the main effects. Simple slope tests (Aiken & West, 1991) showed that participants with an operations role gave lower production quantities ($\beta = -.28.91, t = -$

3.42, $p < .05$) when having a departmental incentive rather than a company incentive ($\beta = -4.03$, $t = -0.47$, n.s.). They also deflated their private forecast more when having a departmental incentive ($\beta = -24.39$, $t = -3.50$, $p < .01$) rather than a company incentive ($\beta = -5.38$, $t = -0.77$, n.s.). Participants with a sales role gave higher production quantities when having a departmental incentive rather than a company incentive, but this difference was not significant. They also generally inflated their forecast independent of the incentive type. This result is illustrated in Figures 4.3 and 4.4.

Figure 4.3: Incentive as a moderator of the relationship between role and production quantity

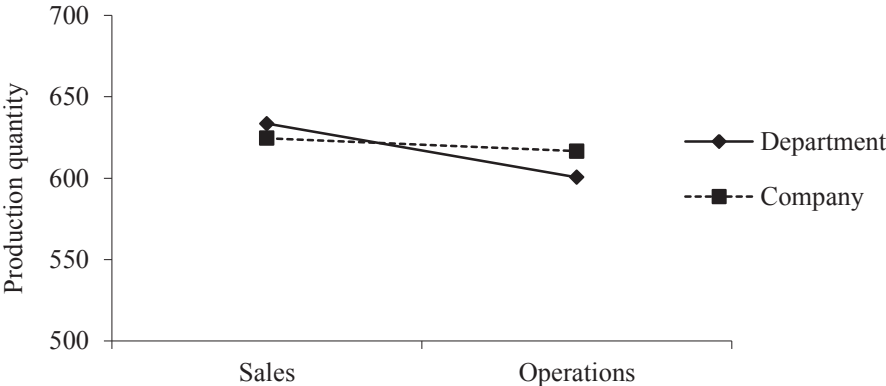
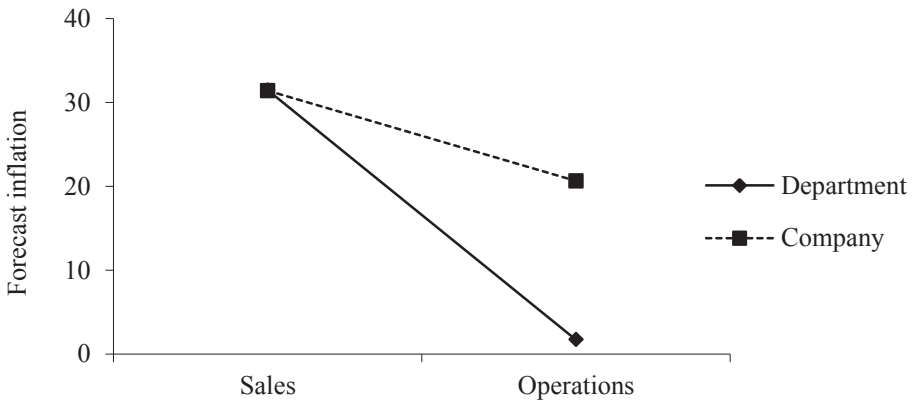


Figure 4.4: Incentive as a moderator of the relationship between role and forecast inflation



Test of mediated moderation. Our next goal was to test whether goal concern for lost sales, goal concern for obsolesces and goal concern for forecast accuracy mediated the moderating effect of incentive type. Mediated moderation occurs when two predictor variables, in our case managerial role and incentive type, interactively affect one or as in this study multiple mediators, which in turn affect an outcome variable (Morgan-Lopez & MacKinnon, 2006). Tables 3a and 3b (model 2, step 3) show that the interaction of managerial role and incentive type was significant in contributing to the mediator goal concern for obsolesces, but not goal concern for lost sales or forecast accuracy. Moreover, goal concern for obsolesces but also goal concern for lost sales, were significant in contributing to forecast, production quantity and forecast inflation in phase 2; see Table 3b, model 4, 5 and 6, step 4. The proposed mediator goal concern for forecast accuracy significantly contributed to production quantity and forecast inflation; see Table 3b, model 5 and 6, step 4. With regard to production quantity and forecast inflation, controlling for the mediators reduced the (marginally) significant regression coefficients of the role-incentive interaction to non-significant levels.

To estimate and test the significance of the conditional indirect effect, we followed the bootstrapping method (with 1000 iterations) proposed by Preacher, Rucker, and Hayes (2007) and refer to the conditional process analysis proposed by Hayes (2013). This procedure tests the null hypotheses that the indirect paths from the interaction of

managerial role and incentive type to the dependent variables forecast, production quantity and forecast inflation via the mediators goal concern for lost sales, goal concern for obsolesces and goal concern for forecast accuracy do not significantly differ from zero.

Separate analyses for forecast, production quantity and forecast inflation supported the significance of the indirect effect of the managerial role-incentive interaction through goal concern for obsolesces on forecast in phase 2 (95% CI = .2939 to 9.3637) and production quantity in phase 1 (95% CI = .3340 to 18.9024) and phase 2 (95% CI = .8303 to 25.5149). These findings illustrate that the interactive effect of managerial role and incentive on forecasting behavior is a function of the goal concern for obsolesces, but not of goal concern for lost sales or forecast accuracy. Thus, Hypotheses 2b was supported whereas we could not find support for Hypotheses 2a and 2c.

4.5 Discussion

Incompatible departmental goals potentially undermine the accuracy of demand forecasts in collaborative forecasting processes. Using insights from research on forecast collaboration and negotiation (Nauta et al., 2002), we predicted that managerial role and incentive type jointly affect forecasting and negotiation behavior because people are concerned with diverging functional goals. Our results show that managerial role and incentive type indeed influenced the concern for particular goals in such a way that sales managers were on average more concerned with lost sales whereas operations managers were more concerned with obsolesces, especially when following a departmental incentive. Following a company-wide incentive led people to be more concerned with forecast accuracy than any of the more functional goals. Results also made clear that production quantities and forecast distortion were more extreme, that is, in line with their functional role descriptions when people had a departmental incentive rather than a company-wide incentive. Goal concern for obsolesces mediated this moderating effect of incentive type on the managerial role–forecast behavior relationship.

Theoretical implications. From a scientific perspective, this research focuses on explaining the causes of human biases that affect performance in an operations

management context (Bendoly, Donohue, & Schultz, 2006; Gino & Pisano, 2008), as it focuses on motivational factors that influence forecast generation in organizations. We aim to make two important contributions. Although forecasting processes in organizations usually rely on inter-departmental coordination, most behavioral research on forecasting has focused on either individual forecasters (Lawrence, Goodwin, O'Connor, & Önkal, 2006), or groups with undifferentiated roles (e.g. Ang & O'Connor, 1991). Our results are in line with previous studies examining the effect of managerial roles on forecast behavior in organizations (Kuo & Liang, 2004; Oliva & Watson, 2009; Önkal et al., 2011). We indeed find departmental biases in forecasts and production quantities. However, the present study extends this line of research and takes a social psychological approach to examine how forecast accuracy can be improved by taking into account how departmental affiliation and goals influence people in their decision-making. Our findings make clear that departmental affiliation exerts its influence on forecast behavior in interdepartmental forecast negotiations through particular functional goal concerns.

Second, combining insights from forecasting as well as social psychology literature, this study extends the scope of the research in behavioral operations management examining motivations and goal structures to define de-biasing strategies instead of identifying gaps between normative models and actual decision-making behavior in operations contexts. In order to devise de-biasing strategies, we need to understand the underlying psychological processes that cause these biases (Katsikopoulos & Gigerenzer, 2013) which, in our case, lead sales and operations managers to over- or under-forecast respectively. Second, a study of motivation in a forecasting task extends the existing work in behavioral operations that often revolves around heuristics and biases and how they affect choices and decisions (Bendoly et al., 2010).

Practical relevance. From a managerial perspective, this study highlights a real-world forecasting problem, that is forecasts in organizations are often used as an instrument to achieve certain outcomes (Wright & Rowe, 2011). Forecasts are also influenced by managerial pressure (Syntetos, Nikolopoulos, Boylan, Fildes, & Goodwin, 2009). Our laboratory setting was sufficient to motivate exactly such purposive forecast behavior and highlights the need to interpret forecasts with care as they are rarely neutral

but influenced by departmental roles. These roles provide a framing effect when forecasters interpret information and make decisions. Furthermore, our results suggest that such deliberate forecast distortion is not only a result of a forecaster's departmental role, but also the type of incentive that a forecaster is having. Different goals and incentive structures motivate people in organizations and may impede integrated solutions in inter-departmental forecast negotiations. A tactic to advance accurate forecasting would be to increase the concern for the opposing department's goal. Organizational structures and processes may affect forecast accuracy directly by creating incentives conducive to collaboration or indirectly through fostering goals and motives which in turn affect forecasting and negotiation behavior. In other words, there is a need to manage the motivations of employees so as to bridge the gap that organizational differentiation creates.

Limitations and future research. The present research raises several questions that merit attention and future research. In our study we found that incentive type and goal concern are important factors in forecast collaboration between the sales and operations departments. We could also show that (departmental versus company) incentives influence the (individual versus. collective) goals that people are concerned with. Interestingly, Nauta et al. (2002) suggested that a prosocial value orientation is related to the concern for goals of another department. While we examined incentives as a means to increase the concern for forecast accuracy, the investigation of the joint effect of incentives and social value orientation could be a fruitful avenue for future research. It is reasonable to assume that prosocial individuals have a high concern for their own as well as the other department's goals even if they have a departmental incentive whereas people with an individualist value orientation will only have a high concern for their own, but not the other department's goal under such circumstances.

It should be noted that our conclusions only apply to dyads in a negotiation context. We chose to include sales and operations as two organizational units in the forecasting process that potentially have the most diverging goals, incentives and planning horizons. However, in practice, the forecasting process may also include members from other departments, for example finance and marketing. Future research could not only extend the number of managerial roles, but also employ face-to-face group discussions instead of

computer-based human-agent interaction. In that case the negotiation can also revolve around departmental issues and priorities (as opposed to the forecast number only) that are relevant for ultimately understanding the motivations that affect forecasting behavior.

Conclusion. Our study advances the work on behavioral forecasting by integrating social psychological research with research on forecasting to disentangle the complex nature of cooperation in social dilemmas in the context of the forecasting process. We identified incentive type as an important organizational factor that broadens our understanding of when departmental affiliation shape a forecaster's perception of forecast negotiations and influence the concern for particular goals that in turn impact the accuracy of demand forecasts.

5 The perception of real versus illusionary trends in time-series forecasting

A central challenge of forecasting from time-series is to distinguish random variation from persistent patterns in the data. Previous research has shown that such judgmental forecasts are subject to a number of systematic errors. A well-documented example is forecasters' tendency to damp trends. We examine the influence of different noise, change and trend levels on forecasters' perception of trends in time-series data. Results from a controlled laboratory experiment show that forecasters detect real trends even when random noise is high as long as persistent change in the level of the time-series is low. Forecasters incorporate illusionary trends into their forecast when time-series are very noisy. Furthermore, the extent to which forecasters damp trends does not only depend on the noise in the time-series, but also the persistent changes in the level. Finally, we identify another type of forecast behavior: the tendency to reverse real trends and trend-like patterns. This allows us to show that the way trends are perceived is more complex than previously thought.

5.1 Introduction

Forecasting in organizations remains an inherently judgmental task. Surveys over the last 10 years have consistently shown that only about 25 percent of companies rely on statistical methods exclusively, with the remaining companies allowing some element of human judgment to influence their forecasts (Fildes & Goodwin, 2007; Fildes & Petropoulos, 2015). Reasons for such reliance on human judgment have little to do with the availability of software. Rather, such reasons are often constructive in nature and relate to incomplete forecasting models not containing important leading indicators of demand such as scheduled promotions or predicted severe weather events (Fildes, Goodwin, Lawrence, & Nikolopoulos, 2009). Some reasons can be less constructive, as decision makers feel the need to influence the forecast to alter the resulting decisions, or they simply do not trust the statistical forecast since the underlying complex algorithm appears

to them as a black-box and causes skepticism (Goodwin, 2002). In either case, the forecasting process in organizations is inherently influenced by human judgement, and thus understanding how human judgement forms in the context of time-series is important for understanding and improving forecasting processes in organizations.

This paper examines how forecasters perceive trends in time-series data. If no real trends are present in a dataset, forecasters can nevertheless spot trends in the inherently random data – a tendency that has been termed as illusionary trend detection (Kremer, Moritz, & Siemsen, 2011). We examine such illusionary trend detection and establish how prevalent it is depending on the degree to which time-series are inherently stable. If real trends are present in the data, the commonly held view is that forecasters will detect such trends, but they will dampen these trends as they extrapolate into the future since the most recent demand acts as an anchor point (Bolger & Harvey, 1993). We also examine such trend dampening behavior, and show that in the dynamic forecasting task we present, trend dampening is only one form of how forecasters react to a trend in a time-series; other forms of behavior include what we term trend reversals, which is possibly a consequence of the gambler's fallacy, i.e. the belief that particular high values average out with particular low values.

We thus study human perceptions of trends in a time-series and present results from a behavioral experiment that systematically varies three characteristics of the demand environment: noise, level change and trend change. Our results are descriptive, in that we do not present a model or hypotheses of how human decision makers will respond to alternative time-series. Yet these results not only firmly document the prevalence of illusionary trend detection, but also show that the way trends are perceived in the data is more complex than previously established. The paper proceeds as follows. The next section discusses relevant literature that relates to our research. We then describe the experimental design and procedure in Section 3, followed by the results in Section 4. Finally, we summarize our findings and conclude this article with suggestions for future research opportunities in Section 5.

5.2 Theoretical background

Most of the existing research on judgmental time-series forecasting has focused on pattern detection. According to Eggleton (1982) forecasters assess the underlying process that has generated the time-series and acquire a cognitive representation of that process in order to extrapolate from past information and make an unbiased forecast. However, people may not actually use this internal representation for forecasting (Harvey, 1988). If people observe variations in demand, they need to separate systematic variation (trends and seasonality) from random noise. Noise poses a particular problem for forecasters to identify the underlying data-generating process. Sanders (1992) provides evidence that performance of judgmental forecasts deteriorates with increasing noise levels. While forecasts should reflect actual patterns but not the random noise in the data, people take into account both when making their forecasts (Harvey, 1995). Psychological research suggests that people have a poor conception of randomness (Ayton, Hunt, & Wright, 1989; Falk & Konold, 1997) and read signals into random changes in time-series (O'Connor, Remus, & Griggs, 1993).

In order to reduce the complexity, people often use heuristics when making judgments under uncertainty (Tversky & Kahneman, 1974). Harvey (2007) provides an overview of forecasting research that shows that people use similar heuristics when making predictions. For example, forecasters employ anchoring and adjustment heuristics when making forecasts from time-series (e.g. Eggleton, 1982). This introduces biases into the forecast because people do not sufficiently adjust away from the last data point of the series that serves as an anchor. This is particularly problematic, if the time-series includes trends. In such situations, forecasters have the tendency to under-extrapolate trends which leads to the phenomenon of trend damping (Bolger & Harvey, 1993; Harvey & Bolger, 1996; Lawrence & Makridakis, 1989). People damp trends in time-series data such that forecasts lie above downward slopes and below upward slopes (Lawrence & Makridakis, 1989). Bolger and Harvey (1993) showed that, if people were required to make more than the one-step-ahead forecast, i.e. up to six-step ahead forecasts, people used their own previous forecast as an anchor instead of the last observation from the data series and did

not adjust for the trend component. Finally, the study by O'Connor et al. (1997) showed that the direction of a time-series including trends and trend changes can make a difference to how accurately people forecast. Forecasts for flat and upward sloping series were better than those for downward sloping series. Furthermore, greater trend damping occurred for downward sloping series, which can possibly be explained by participants' expectations to reverse downward trends, but not upward trends.

Besides the heuristics explanation, adaptation may explain trend damping. Reimers and Harvey (2011) explored the extent to which people are sensitive to autocorrelation in time-series and to what extent biases and contextual variables affect judgment. Results from three experiments showed that people perceive the degree of autocorrelation in time-series data, but they also seemed to perceive positive autocorrelation in uncorrelated time-series. The study shows that people's judgment is affected by the knowledge about natural time-series such as population growth, which initially tend to accelerate, but eventually the growth becomes damped. Further support for this ecological explanation of trend damping comes from Harvey and Reimers (2013) who report results from three experiments that demonstrate that trend damping cannot be attributed to under-adjustment. Instead the authors suggest an alternative explanation that people come across trends in their natural environment, which do not persist over time. People take this experience of damped trends in their natural environments into account when making forecasts.

In contrast to most research on trend damping that tries to explain the occurrence of this effect, our research focuses on the specification of forecast patterns. In addition to trend-damping, one other forecast pattern has already been identified by Harvey and Reimers (2013) who showed that people exhibit anti-damping (forecasts that are more extreme than the upward or downward sloping trend lines), especially for decelerating functions and for linear series with shallow slopes. This calls into question whether more patterns may actually exist. Some evidence for additional patterns also comes from the research on regime change that has shown that people tend to predict that trends will reverse in the future, if they observed such reversals in the past even if they were told that the time-series follows a random walk (Bloomfield & Hales, 2002). However, this regime shifting behavior does not seem to be universal. Asparouhova, Hertzfel and Lemmon

(2009) found that the length of a streak impacts the likelihood with which participants predict future reversals. For short streaks, people were more likely to predict reversals whereas for long streaks people were more likely to predict continuation. Although this research is informative, it applies to binary outcomes and time-series that actually do not contain systematic variations. It appears that the perception of trends seems to depend on variations in the change and noise level of a time-series (Kremer et al., 2011). Thus, the central question of our research is under what conditions do people detect actual trends and inadequately react to illusionary trends.

5.3 Method

In this study, we build on and extend the experimental design that Kremer et al. (2011) used in an earlier study on behavioral forecasting. Participants were randomly assigned to one of six experimental conditions representing different demand environments characterized by the three systematically varying parameters change c , noise n and trend r . The latter is an extension of the original Kremer et al. (2011) design that included the change and noise components, but no trend component.

Demand environment. As in Kremer et al. (2011), forecasts are made in each period t after observing demand D_t . No additional information on future demand is provided apart from the information contained in the time-series $D_t = \{D_t, D_{t-1}, D_{t-2}, \dots\}$. The demand process follows:

$$D_t = \mu_t + \varepsilon_t \quad (1a)$$

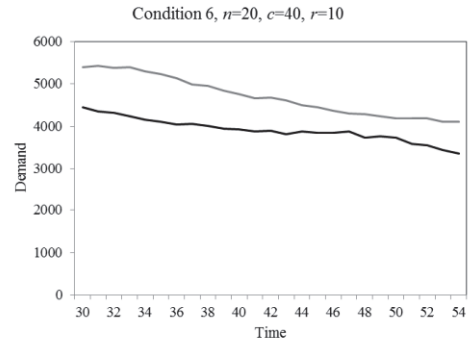
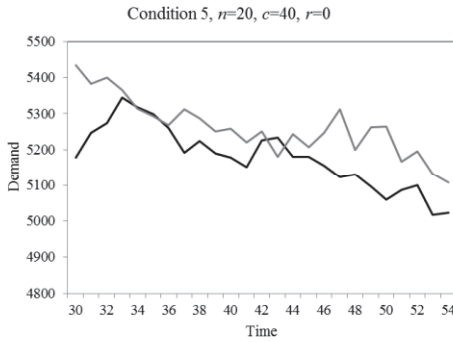
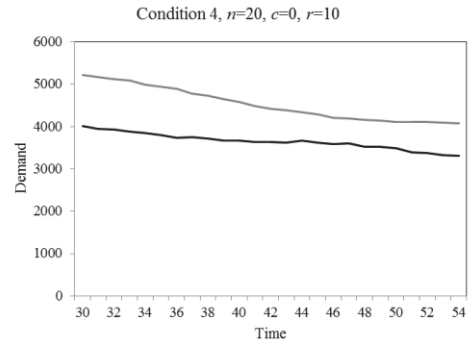
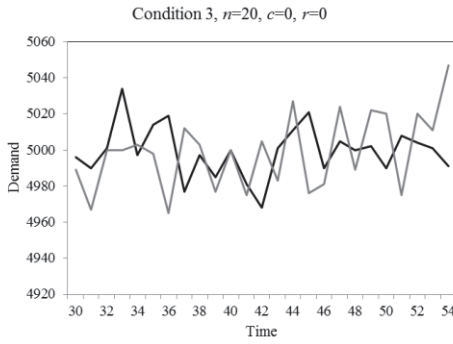
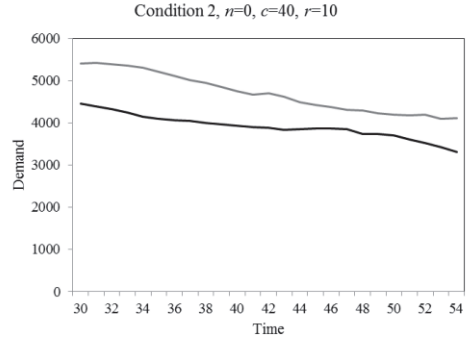
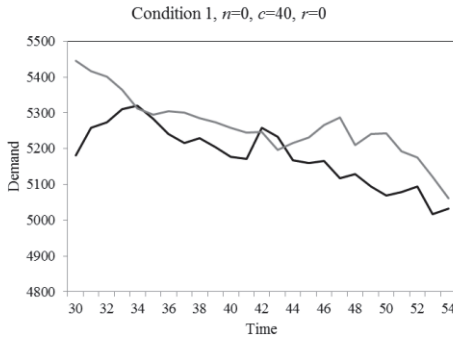
$$\mu_t = \mu_{t-1} + \tau_{t-1} + v_t \quad (1b)$$

$$\tau_t = \tau_{t-1} + \lambda_t, \quad (1c)$$

where $\varepsilon_t \sim N(0, n^2)$, $v_t \sim N(0, c^2)$ and $\lambda_t \sim N(0, r^2)$ are independent random variables. Thus, the time-series contains three types of components: temporary shocks (through ε_t – termed *noise* throughout) and permanent shocks (through v_t and λ_t – termed *change* and *trend* throughout, respectively). The standard deviation c captures the change in the true, unobserved level μ_t and the standard deviation r captures the trend in the level,

that is, permanent shocks of the time-series that persist in subsequent periods. The standard deviation n captures the noise surrounding the level, that is, temporary shocks to the time-series that last for a single period. Figure 5.1 provides example datasets with different values of n , c and r to illustrate the parameter's influence on the shape of the time-series.

Figure 5.1: Example demand times-series for different n , c , and r



Optimal forecast. The optimal forecast F_{t+1}^* (made in period t for the following period $t + 1$) for a time-series without trend follows the single exponential smoothing method (Muth, 1960),

$$F_{t+1} = F_t + \alpha(D_t - F_t), \quad (2)$$

where the previous forecast F_t is adjusted towards the most recent demand observation D_t , and the magnitude of the adjustment depends on the forecast error $E_t = D_t - F_t$ and the weight α , that is placed on that error. The forecast will be more strongly revised, the larger the forecast error. The weight depends on the underlying parameters of the demand environment, that is, the change (c) and noise (n) parameters, which define the change-to-noise ratio $W = c^2 / n^2$. If variations in demand result mainly from noise (low values of W), forecast errors should not influence the forecast. If variations in demand represent actual changes in the level of the series (high values of W), forecast errors should be taken into account for the new forecast (for an elaboration of that intuition, see Harrison, 1967). The optimal smoothing parameter α^* and can be formalized as:

$$\alpha^* = \frac{2}{1 + \sqrt{1 + 4W^{-1}}} \quad (3)$$

Combining the optimal forecasting method in Equation (2) with the optimal parameter in Equation (3) yields the optimal forecast strategy for our non-trend demand environment,

$$F_{t+1} = F_t + \alpha^*(W)(D_t - F_t). \quad (4)$$

For trend-time-series, the optimal forecast follows a two-step approach using the double exponential smoothing. First, the current level L_t is estimated comparable to Equation (4) by,

$$L_t = F_{t-1} + \alpha(D_t - F_{t-1}). \quad (5)$$

Second, the current trend T_t is estimated using

$$T_t = T_{t-1} + \beta(L_t - L_{t-1} - T_{t-1}). \quad (6)$$

Combining the two estimates, the forecast for the upcoming period is

$$F_{t,t+n} = L_t + n T_t \quad (7)$$

Following Harrison (1967), the optimal smoothing parameters α^*, β^* can be found solving

$$\beta^2 W_1 = 1 - \alpha \quad (8)$$

$$\beta^2 W_2 = \alpha^2 + \alpha \beta - 2\beta, \quad (9)$$

where $W_1 = n^2/r^2$ and $W_2 = c^2/r^2$.

Experimental design. In line with the setup of the experiment in Kremer et al. (2011), participants were required to make sequential forecasts based on consecutive time-series demand signals which were generated from a random walk with noise. Participants were provided with 30 periods of demand history and were asked to make a forecast for one, two and three periods ahead in each of 25 successive periods. Throughout the experiment, participants were also provided with a graph that displayed demand up the current period and updated automatically. Additionally, a table included past demand, previous forecasts, and absolute forecast errors.

We varied the degree of change by setting c equal to 0 or 40. Second, we varied the degree of noise by setting n equal to 0 or 20. Finally, we varied the degree of trend by setting r equal to 0 or 10. For each condition, we generated two demand data sets for each of the six conditions that all started with the same 30 periods of historic demand. An overview of the experimental conditions and number of participants N in each condition is provided in Table 5.1. This resulted in a between-subject design with $6 \times 2 = 12$ data sets.

Table 5.1: Overview of experimental conditions

Condition	n	c	r	N
1	0	40	0	13
2	0	40	10	13
3	20	0	0	12
4	20	0	10	20
5	20	40	0	21
6	20	40	10	21

The experiment was conducted at a behavioral lab in a large public university in the US. The 102 participants were undergraduate students and completed the experiment as part of an operations course at the business school. Two participants had to be excluded from the analysis because of missing data. Of the 12 data sets, 4 data sets have 6 participants, 2 data sets have 7 participants, 4 data sets have 10 participants, and the remaining 2 data set have 11 participants.

5.4 Results

Initial analyses. Table 5.2 provides an overview of the observed mean absolute error MAE for the 1-, 2-, and 3-step ahead forecasts $MAE(D_t, F_{it}) = \left(\frac{1}{SIT}\right) \sum_{SIT} |F_{sit} - D_{sit}|$, that is the average across all t periods, I subjects in both S demand data sets over all conditions. Simple t -tests show that the observed mean absolute error for the 1-step ahead forecast ($MAE1$) is significantly larger than the corresponding mean absolute error based on optimal forecasts for conditions 1 ($p < .05$), 4 ($p < .01$), and 6 ($p < .01$). For the 2- and 3-step ahead forecasts, the observed mean absolute error ($MAE2$ and $MAE3$) is significantly larger than the optimal mean absolute error for all conditions ($p < .01$), with the exception of condition 3 where the difference in mean absolute error is not significant. A comparison across conditions is consistent with earlier research that has shown that performance deteriorates with increasing noise and change levels (Kremer et al., 2011;

Sanders, 1992). Furthermore, participants perform better in demand environments that do not contain trends. Finally, results show that (with the exception of $MAE2=18.14$ and $MAE3=18.23$ in condition 3), forecast performance deteriorates with increasing time horizon, both for the trended and untrended series which partly contradicts results from Bolger and Harvey (1993) who find increasing forecast errors only for trended series, but not untrended series as the forecast horizon is extended.

Table 5.2: Observed forecasting performance by MAE

<i>MAE1</i>					
r=0	n=0	n=20	r=10	n=0	n=20
c=0	N/A	20.28 (18.02)	c=0	N/A	31.84 (25.97)
c=40	38.59 (30.44)	58.64 (39.07)	c=40	43.88 (36.32)	61.04 (41.17)

<i>MAE2</i>					
r=0	n=0	n=20	r=10	n=0	n=20
c=0	N/A	18.14 (18.30)	c=0	N/A	48.04 (39.72)
c=40	62.38 (48.43)	65.88 (50.16)	c=40	77.69 (62.76)	99.72 (64.84)

<i>MAE3</i>					
r=0	n=0	n=20	r=10	n=0	n=20
c=0	N/A	18.23 (18.26)	c=0	N/A	70.30 (59.18)
c=40	75.29 (55.62)	74.77 (59.01)	c=40	112.26 (90.54)	137.54 (90.51)

Results of a multivariate analysis of variances showed that the different levels of noise, change and trend yielded different performance for the 1-step ahead forecast (FC1), $F(5,99) = 5.39, p < .001, \eta = .22$, the 2-step ahead forecast (FC2), $F(5,99) = 43.20, p < .001, \eta = .70$, and the 3-step ahead forecast (FC3), $F(5,99) = 51.43, p < .001, \eta = .73$. Conditions 3 and 4 consistently yielded the lowest mean absolute error for the three forecasts. These are the two conditions without change. On the contrary, condition 6 which

include high noise, change and trend consistently yielded the highest mean absolute error for the three forecasts.

Pattern identification. For each observation, we classified the sequence of the 1-, 2-, and 3-step ahead forecasts (FC1, FC2 and FC3) in terms of their direction relative to the previous step forecast. We identified four major patterns that these three forecasts display. We termed them *trend*, *trend damping*, *trend reversal* and *constant*. In the trend category, the three forecasts increased/decreased with either the same or an increasing positive or negative growth rate. In the trend damping category, the three forecasts exhibit an upward or downward trend which becomes smaller with increasing time horizon. In the trend reversal category, the forecast first increases/decreases and then turns in the opposite direction while overall a positive/negative trend over the whole 3 periods can still be observed. In the constant category, at least two of the forecasts are constant. The four major patterns with their subcategories are displayed in Figure 5.2 for upward and downward sloping time-series.

Of the 2500 observations, 813 belonged to the trend category, 772 to the trend damping category, 749 to the trend reversal category, and 166 to the constant category. Consistent with earlier research (Harvey & Reimers, 2013), we find trend damping. However, we also obtain a large number of different patterns. More than half of the participants (53 percent) displayed one dominant pattern that they used in 13 or more of the 25 required forecast sequences. Apart from condition 6, we obtain one dominant pattern in each condition as shown in Table 5.3.

Figure 5.2: Forecast patterns

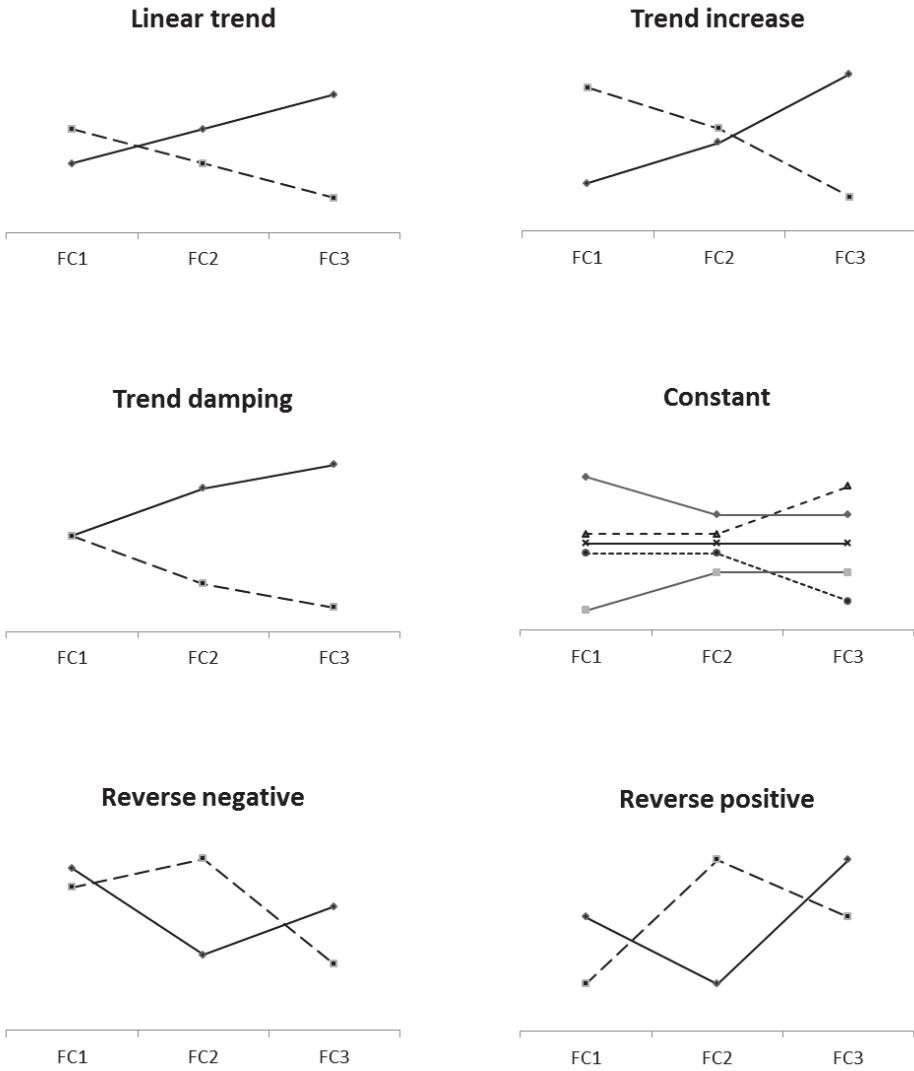


Table 5.3: Pattern distribution across conditions

Condition	Trend	Trend damp	Reversal	Constant	Total
1	112	94	93	26	325
2	105	148	42	30	325
3	59	62	155	24	300
4	229	160	92	19	500
5	121	117	231	56	525
6	187	191	136	11	525
Total	813	772	749	166	2500

We primarily find the trend pattern in conditions 1 and 4. The trend damping pattern can primarily be found in conditions 2 as well as 6. Finally, the trend reversal pattern is mostly shown in conditions 3 and 5. In condition 1, which contains high change, but no noise or trend, people seem to misperceive the change signals as trend patterns. In condition 4, which contains trend and noise, people still correctly identify trends. In condition 2, which contains high change and trend, but no noise, and condition 6, which contains noise, change and trend, people adequately perceive the trend, but damp it. As soon as there is noise and possibly change, but no trend, people do not explicitly display a trend pattern, but reverse their forecasts instead. This pattern overview is shown in Table 5.4.

Table 5.4: Dominant pattern per condition

r=0	n=0	n=20
c=0	N/A	reversal
c=40	trend	reversal
r=10	n=0	n=20
c=0	N/A	trend
c=40	trend damp	trend damp

5.5 Discussion and Conclusion

This research compares forecast behavior across different demand environments in order to identify under what conditions forecasters correctly perceive actual trends in time-series, underestimate trends or incorporate illusionary trends into their forecasts. Our results show that the occurrence of illusionary trends is prevalent in environments characterized by low noise and high change. As noise increases, this faulty perception of non-existing trends decreases. This finding is in line with Kremer et al. (2011) who argue that noise obscures the false impression of trend-like changes in the level. Conversely, forecasters correctly identify actual trends in demand environments characterized by low change and high noise levels. This seems to suggest that, given a trended time-series, a forecaster can distinguish random variation from actual patterns in the data and detect trends, as long as additional persistent change in the level of the time-series is low. We also obtain trend damping effects for the trended time-series that either only contain noise or both change and noise. Combined with the insight that people correctly identify trends under low noise/high change levels, this seems to suggest that the phenomenon of trend damping cannot merely be attributed to increasing noise levels as has been suggested previously (Harvey & Reimers, 2013). Instead, the occurrence of trend-damping seems to depend on persistent changes in the level as well. In addition to previously established forecast patterns, we identified another pattern that we termed trend reversal. This pattern is prevalent in untrended time-series with high noise levels, irrespective of changes in the level, but it also persists in time-series that contain trends.

Our study is, to the best of our knowledge, the first study to demonstrate illusionary trend detection in judgmental time-series forecasting. The design of our experimental conditions allowed us to analyze the (false) perception of trends in detail under different demand conditions producing actual trends as well as trend-like sequences. Furthermore, our results suggest that people not only damp trends such that forecasts lie below upward trend lines and above downward trend lines (Lawrence & Makridakis, 1989), but also reverse trends that they observe. This behavior can possibly be attributed to the belief that

high values are followed by low values, also known as the gambler's fallacy or "hot hand" phenomenon (Rabin & Vayanos, 2010).

Our study also has several limitations. Previous research has shown that the direction of a time-series has an effect on trend damping behavior which was most pronounced in downward series (O'Connor et al., 1993). The time-series in the present study were all downward sloping series. Furthermore, we systematically varied the degree of noise, change and trend in the data such that it was either absent or present. As such the demand process was more complex than a simple stationary process and representative of real-life forecasting contexts. Nevertheless, a more refined setup with both upward and downward series including low, medium and high levels of noise and change and varying trend strengths (as has been used by Harvey & Reimers, 2013; and Thomson, Pollock, Gönül, & Önköl, 2013) should be used to further refine our understanding of the perception of trends in time-series data. Finally, the series containing actual trends could be varied in terms of the length of a streak to investigate whether the trend reversal pattern occurs more often for short streaks as suggested by research on regime shifting behavior (Asparouhova et al., 2009).

Our findings have implications for forecasting practitioners in a variety of forecasting contexts. In practice, forecasters often use historic data, for example past sales or growth in market share, and extrapolate that information to determine possible trends in the future. Clearly, acting on perceived trends, that actually do not exist, can reduce forecast accuracy and have detrimental consequences for a number of planning decisions. Our findings suggest that decision-makers cannot always clearly distinguish actual from illusionary trends and persistent changes from random variations in time-series.

6 General Discussion

Forecasting plays a pivotal role in organizations in order to match demand and supply. Failing to achieve a match can affect the short- and long-term profitability of companies (Hendricks & Singhal, 2005; Hendricks & Singhal, 2009). Whereas early forecasting research thought of human judgment as detrimental to forecast accuracy, it is nowadays recognized as an indispensable decision aid complementing statistical methods of forecasting (Fildes & Goodwin, 2007; Sanders & Manrodt, 2003). However, human judgment in operational decision-making is subject to a number of biases (Gino & Pisano, 2008) and forecasters employ various heuristics to make predictions when using their judgment (Harvey, 2007). Therefore, it is important to consider human judgment in forecasting to attenuate negative consequences of poor forecasts for many related operational decisions. Despite this, only a small amount of research on forecasting focusses on the influence of heuristics and biases on forecast accuracy (Lawrence, Goodwin, O'Connor, & Önkal, 2006). This dissertation aimed at shedding some light on this issue. In four empirical chapters, we attempted to provide insights that may clarify the human factor in forecasting. In doing so, we have merged different strands of literature by combining traditional forecasting literature with concepts from agency theory, social dilemma and negotiation, and psychology. First, we will discuss the contribution of each chapter to the forecasting literature. Second, we will discuss the implications of this dissertation for practice. We conclude this chapter and dissertation by providing directions for future research.

Theoretical implications. Chapter 2 contributes to the forecasting literature in at least three ways. The main purpose of this study was to explore the role of forecast ownership in a cross-functional forecasting process and how a real organization attempted to address forecast biases rooted in functional differentiation and incentive misalignment. Hence, the focus of this chapter is on intentional biases that distort forecasts in line with departmental goals and agendas. Our findings revealed that forecast ownership can be a means to improve forecast accuracy while, at the same time, it can increase the conflict between the different departments involved in the planning process. A more holistic

approach to integrate the departmental forecasts, on the other hand, was found to be successful in managing the intentional biases even though the diverging incentives remained unchanged. This study extends the forecasting literature by conceptualizing the forecasting process as a social dilemma (Messick & McClintock, 1968; Van Lange & Kuhlman, 1994), an idea that so far has only been used to help understand supply chain partnerships *between* firms (McCarter & Northcraft, 2007; McCarter & Kamal, 2013), but not supply chain collaborations *within* firms. Second, this study complements extant literature on forecast combination (Armstrong, 2001; Sanders & Ritzman, 2004) that often lacks the organizational context which we consider by exploring how differential roles of forecasters shape forecasting behavior. Finally, we developed a novel theoretical concept which we termed *forecast ownership* and propose that feelings of ownership can emerge with respect to a forecast as we observed a form of psychological ownership (Pierce, Kostova, & Dirks, 2001) among the departments that did not possess formal forecast ownership.

In Chapters 3 and 4, we built on the findings of Chapter 2 and simplified the context of the collaborative forecasting process that we studied in a real organization to a dyadic situation that we put into two laboratory based experiments. The major contribution of the first experiment is that we studied the relationships between a forecaster's departmental affiliation and social motives and forecasting behavior. As such our findings significantly extend our theoretical understanding of forecasting behavior in interdependent situations. We demonstrate that departmental affiliation influenced forecasting behavior such that people with an assigned operations role on average gave lower forecasts than those with a sales role, and that the extent of this forecast distortion depends on a person's social value orientation (SVO). The results of this study relate to the growing literature on the role of managerial frames in forecasting (Kuo & Liang, 2004; Oliva & Watson, 2009; Önköl, Lawrence, & Zeynep Sayim, 2011). However, these managerial frames do not seem to have a universal effect on forecasting behavior. Instead, a person's disposition towards cooperation or conflict helps explain forecasting behavior, taking the social context surrounding the forecasting process into account.

The experiment in Chapter 4 further investigated the effect of a forecaster's departmental affiliation on forecasting behavior. In particular, we explored the related issue to what extent different incentives are related to accurate forecasts and credible forecast information sharing. Our findings highlight the joint effect of departmental affiliation and incentive. Specifically, we showed that sales managers were on average more concerned with lost sales whereas operations managers were more concerned with obsolesces, especially when following a departmental incentive. The major contribution of this study is that we show that departmental affiliation exerts its influence on forecasting behavior in interdepartmental forecast negotiations through being concerned with particular functional goals. As such our findings help understand the underlying psychological processes that cause forecast biases and thus devise de-biasing strategies (Katsikopoulos & Gigerenzer, 2013). By taking the motivational orientation of decision-makers into account both experiments in Chapters 3 and 4 generally extend the scope of existing research in behavioral operations management that mainly revolves around identifying decision-making biases in operations (Bendoly, Croson, Goncalves, & Schultz, 2010).

In Chapter 5, we turn to the individual perspective in forecasting and explore how forecasters actually perceive trends in time-series data. Specifically, we identify different forecast patterns that forecasters exhibit under varying demand conditions. While we find previously established patterns, such as trend damping (Bolger & Harvey, 1993; Harvey & Reimers, 2013), we also find a pattern that we termed *trend reversal* that has not been researched yet. Moreover, we provide an empirical basis for the prevalence of illusionary trend detection, a tendency that has not been rigorously explored in previous literature (Kremer, Moritz, & Siemsen, 2011). Our study suggests that the way trends are perceived in time-series data is more complex than previously thought.

Practical relevance. Forecasting is crucial for supply chain planning and the match of demand and supply. Most organizations use some form of judgment in their forecasting processes (Fildes & Goodwin, 2007) and forecast decisions are often made in groups (Lawrence et al., 2006). In the practitioner literature this process is commonly known as Sales and Operations Planning (S&OP) process (Singhal & Singhal, 2007). A central

challenge of collaborative forecasting within firms is to pool the decentralized knowledge about demand and supply that exists throughout the company and is often biased by human judgment (Kremer, Siemsen, & Thomas, 2012). This dissertation suggests that assigning forecast ownership to one organizational department that assumingly has the highest vested interest in producing accurate forecasts does not necessarily eliminate the systematic forecast biases to over- or under-forecast inherent in functional differentiation. Instead, both intentional and unconscious biases which are introduced into the forecasting process through human judgment can be minimized by properly understanding the underlying motivational and cognitive processes.

Specifically, our studies demonstrate that, in organizational forecasting, the departmental role of a forecaster frames the way in which a forecaster interprets information and makes decisions. For that reason, forecasts can rarely be considered neutral. Different goals and incentive structures motivate people and may impede integrated solutions in inter-departmental forecast negotiations. It is therefore paramount for organizations to manage the motivations of employees so as to bridge the gap that organizational differentiation creates. One way to achieve that is by directly creating incentives conducive to collaboration or by indirectly fostering goals and motives which in turn affect forecasting and negotiation behavior. It is particularly promising that, if formal incentives are destructive for collaboration and cannot be changed, an individual's disposition towards cooperation can still enhance collaboration among different departments. Thus, managerial interventions should aim at the selection of employees in such a way that their personalities and behaviors 'fit' strategically communicated negotiation outcomes, and to establish a match between individual as well as common (organizational) interests.

In practice, forecasters often use historic data and extrapolate that information to determine possible trends in the future. In these situations, forecasters also use heuristics when making predictions. Clearly, acting on trend-like patterns, that in fact are random variations in the time-series, can reduce forecast accuracy and have detrimental consequences for a number of planning decisions. Our findings suggest that decision-

makers cannot always clearly distinguish actual from illusionary trends and persistent changes from random variations in time-series.

Future research. The four studies in this dissertation integrated a broad array of literature, employed different research methods and focused on different units of analyses: groups, dyads and the individual decision-maker. The results of all four studies relate to the growing literature on behavioral operations management, particularly focusing on forecasting. Despite their theoretical and practical contributions, the studies in this dissertation also suffer from limitations and raise several questions that merit attention and future research to expand our understanding of the human factor in forecasting, specifically the underlying motivational and cognitive processes that shape forecasting behavior.

While the case study in Chapter 2 offered valuable insights to propose a novel theoretical concept, more case-based research should further develop and refine the concept of forecast ownership and elaborate on the dynamics between owners and non-owners. An interesting avenue for future research would also be to compare cases in which the forecast owner is located in different organizational departments, such as Finance instead of Supply Chain or a neutral entity as suggested by Oliva and Watson (2011). Forecast tournaments with students or managers may offer a good alternative to test theoretical propositions (Tetlock, Mellers, Rohrbaugh, & Chen, 2014), if access to real organizations is difficult to obtain.

With the two experiments in Chapters 3 and 4, we were able to establish the importance of social value orientation and goal concern in inter-departmental forecast negotiations. Nevertheless, our conclusions apply to dyadic situations, whereas in reality the forecasting process may include various departments. Moreover, our negotiations context in both experiments was rather simplified in that participants negotiated with a computer agent and not another real human being. In a more complex interdependent negotiation, whether computer-based or face-to-face, the negotiations could revolve around departmental issues and priorities (as opposed to the forecast number only) that are relevant for ultimately understanding the motivations that affect forecasting behavior, and that are more representative of real forecasting processes in organizations. While we examined social value orientation and incentives separately in the two experiments, the

investigation of their joint effect could be a fruitful avenue for future research. It is reasonable to assume that prosocial individuals have a high concern for their own as well as the other department's goals, even if they have a departmental incentive, whereas people with an individualist value orientation will only have a high concern for their own, but not the other department's goal under such circumstances. Previous research suggests that interdepartmental negotiations and problem-solving behavior in conflict situations are indeed influenced by individual, relational and organizational factors (Nauta & Sanders, 2000).

Finally, earlier research on human perception of trends in time-series data assumed that people detect but damp trends that actually exist in the data (Harvey & Reimers, 2013). Our study provides evidence for additional forecast patterns that people exhibit when making predictions from trended time-series. Moreover, we provide empirical evidence for the phenomenon of illusionary trend detection in judgmental time-series forecasting. While we used a rigorous experimental design, there is an opportunity to extend the experiment by comparing downward-with upward-sloping time-series and refine the variation of the different time-series parameters: noise, change and trend, as well as the length of actual patterns in the data.

Concluding remark. In this dissertation, I set out to shed light on the human factor in forecasting. I found that organizational roles, that is being a member of a particular department, provide a strong frame for the way in which people interpret information and make decisions in collaborative forecasting processes. A key take-away from this research is that forecasts in organizations are rarely neutral and often serve a certain purpose other than predicting future sales. This is unfortunate, if one considers the importance of matching demand and supply for organizational survival. As reducing functional differentiation or changing dysfunctional incentives are often not a viable option, our findings that highlight the importance of motivational orientations in such interdependent forecasting processes are promising. Furthermore, I discovered that already on the individual level, human judgment in making predictions can be erroneous. I am convinced that understanding the underlying cognitive and motivational processes is paramount to devising strategies for more accurate forecasts. I hope others will build on the findings of

this dissertation and explore related intriguing research questions that certainly still exist to further expand and establish behavioral operations management as a research discipline.

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Summary in English

Prior academic research has recognized human judgment as an indispensable decision-aid in demand forecasting although it is subject to a number of biases. Therefore, it is important to understand human judgment in forecasting to explain poor forecast decisions and attenuate their negative consequences for many related operational decisions. This dissertation is part of a growing research field in which human behavior and cognition are incorporated into analytical models of operations management. It bundles four empirical studies on demand forecasting, using a variety of research methods and units of analysis. These studies provide new insights into the role of human judgment in demand forecasting.

The functional specialization and differentiation inherent to most organizations usually shapes forecasting behavior in such a way that it benefits departmental goals and agendas. Lack of clear forecast ownership, diffused responsibilities and varying interests and incentives are often at odds with the organizational goal of producing accurate forecasts. We identify and describe the potential benefits of forecast ownership and mechanically combined departmental forecasts on the tendency to over- and under-forecast demand. Giving people the opportunity to have a say in the forecast, to invest time and energy in the forecasting process, and disseminating information and knowledge about the forecast and the forecasting process are all means to improve the involvement and commitment from non-owning stakeholders in the forecasting process.

The findings in this dissertation also show that departmental roles, for example being a member of a Sales or Operations Department, offer a particular frame with which forecasters interpret information and make decisions. However, the effect of departmental affiliation on forecast accuracy depends on a forecaster's individual disposition towards cooperation and conflict. Prosocial individuals are less likely than proself individuals to deliberately bias forecasts in forecast negotiations. Our studies suggest that framing interdepartmental forecast negotiations as cooperative, encouraging discussions between departments to understand the impact of individual decisions on others as well as allowing

time for negotiation to converge opinions could all bridge the gap that organizational differentiation creates.

Human judgment in demand forecasting can also be erroneous, especially when forecasters use historic data and extrapolate that information to determine possible trends in the future. Such situations are not characterized by organizational differentiation that may bias forecasts. Instead, forecasters use heuristics to make decisions. This dissertation shows that forecaster act on trend-like patterns that, in fact, are random variations in the time-series. It seems that people cannot clearly distinguish actual from illusionary trends and persistent changes from random variations in time-series. Our results indicate that forecasters should be aware of their tendency to read system into noise and to underestimate trends. Finally, decision support systems should provide appropriate presentation modes and allow for the decomposition of the different components of a time-series to help forecasters make accurate predictions.

Samenvatting (Summary in Dutch)

Wetenschappelijk onderzoek heeft het menselijk oordeel erkend als een onmisbare beslissingshulp bij vraagvoorspellingen, ondanks het feit dat menselijk gedrag en beslissingen lijden onder een aantal heuristieken. Het is daarom belangrijk om negatieve gevolgen van het menselijk oordeel te begrijpen en slechte voorspellingen en gerelateerde operationele beslissingen te vermijden. Dit proefschrift maakt onderdeel uit van een groeiend onderzoeksdomein waarin menselijk gedrag en cognitie in analytische modellen van Operations Management in acht worden genomen. Het voegt vier empirische studies samen waarin de rol van menselijk gedrag op vraagvoorspellingen wordt getoetst, met behulp van verschillende onderzoeksmethoden.

De functionele specialisatie in organisaties beïnvloedt vraagvoorspellingen op een manier dat departementale doelen en agenda's er baat bij hebben. Zowel gebrek aan duidelijke verantwoordelijkheden als verschillende interesses en motieven staan vaak in de weg van nauwkeurige vraagvoorspellingen. We identificeren en beschrijven de mogelijke voordelen van het geven van duidelijke verantwoordelijkheden en het gebruiken van mechanisch gecombineerde vraagvoorspellingen op de neiging voorspellingen te hoog of te laag te stellen. Wanneer mensen de mogelijkheid krijgen om invloed uit te oefenen op de vraagvoorspelling, informatie en kennis over het voorspellingsproces te verwerven, en informatie ontvangen over het voorspellingsproces, kan dit de betrokkenheid van stakeholders verbeteren.

De resultaten van dit proefschrift maken tevens duidelijk dat de departementale rollen een bepaald perspectief bieden waarmee mensen informatie interpreteren en beslissingen nemen. Echter, het effect van de departementale aansluiting op nauwkeurige voorspellingen is afhankelijk van de individuele neiging ten aanzien van samenwerking en conflict. Onze studies laten zien dat coöperatieve onderhandelingen en discussies tussen afdelingen het begrip voor de invloed van individuele beslissingen op anderen kunnen verbeteren.

Menselijk oordeel bij vraagvoorspelling kan ook verkeerd uitwerken, bijvoorbeeld wanneer mensen gebruik maken van historische gegevens en die informatie extrapoleren

om mogelijke ontwikkelingen in de toekomst te bepalen. In dergelijke situaties maken mensen gebruik van heuristieken om beslissingen te nemen. Dit proefschrift toont aan dat mensen willekeurige variaties in tijdreeksen als trend-achtige patronen interpreteren. Het lijkt erop dat mensen geen duidelijk onderscheid kunnen maken tussen werkelijke en illusionaire trends. Tot slot zouden besluitvormingssystemen moeten voorzien in goede presentatie modellen, en het mogelijk moeten maken om de verschillende onderdelen van tijdreeksen te onderscheiden, om zodoende mensen die voorspellingen maken te helpen dit zo accuraat mogelijk te doen.

About the Author



Stefanie Brix, née Protzner was born on October 16th, 1983 in Berlin, Germany. She obtained her Bachelor's degree in Psychology from University of Konstanz, Germany in 2007, where she has been active as chairwoman of the local IAESTE (International Association for the Exchange of Students for Technical Experiences) committee in 2006/2007. In the summer of 2008, Stefanie moved to Rotterdam to complete the General Management Program and graduated (cum laude) with a Master of

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MIND THE GAP BETWEEN DEMAND AND SUPPLY A BEHAVIORAL PERSPECTIVE ON DEMAND FORECASTING

Prior academic research has recognized human judgment as an indispensable decision-aid in demand forecasting although it is subject to a number of biases. Therefore, it is important to understand human judgment in forecasting to explain poor forecast decisions and attenuate their negative consequences for many related operational decisions. This dissertation bundles four empirical studies on demand forecasting and is part of a growing research field in which human behavior and cognition are incorporated into analytical models of operations management.

The functional specialization and differentiation inherent to most organizations usually shapes forecasting behavior in such a way that it benefits departmental goals and agendas. Lack of clear forecast ownership, diffused responsibilities and varying interests and incentives are often at odds with the organizational goal of producing accurate forecasts. We identify and describe the potential benefits of forecast ownership and mechanically combined departmental forecasts on the tendency to over- and under-forecast demand. The findings in this dissertation also show that departmental roles offer a particular frame with which forecasters interpret information and make decisions. However, the effect of departmental affiliation on forecast accuracy depends on a forecaster's individual disposition towards cooperation and conflict. Our studies suggest that it is paramount for organizations to manage the motivations of employees so as to bridge the gap that organizational differentiation creates. One way to achieve that is by directly creating incentives conducive to collaboration or by indirectly fostering goals and motives which in turn affect forecasting and negotiation behavior.

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