The folly of forecasting:
The effects of a disaggregated sales forecasting system on sales forecast error,
sales forecast positive bias, and inventory levels

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ABSTRACT

In this study we provide field evidence of the role that sales forecasts play as the coordination mechanism between sales managers and production managers. An extensive body of operations research documents the negative consequences of sales forecast error and investigates how to respond to sales forecast error by optimizing inventory “buffer” stocks. In contrast, we focus on whether a change in the sales forecasting information environment implemented at our research site reduces forecast error and, hence, the need for those buffer stocks. The newly implemented sales forecast “contingency system” disaggregated the sales forecast into two components: (i) an official sales forecast that reflected relatively more certain expected demand, and (ii) a separate report that provided the probability of a contingent demand “event” occurring and the expected volume impact of that event. We predict and find that the system had the intended effect of a reduction in inventory levels, both through better timing of production via a production “postponement” strategy and through a decrease in absolute forecast error. We further consider the incentives of the self-interested sales managers and predict and find that the inventory reduction benefits of the sales forecast system gained through postponement and a decline in absolute forecast error were partially offset by an increase in positive sales forecast bias. Our study provides novel insights regarding the role of forecasting within the organizational context. While the operations literature uses analytic and simulation methods to examine sales and operations planning in a very mechanistic way, we examine the role that changes in the sales forecast information environment play and the opportunistic responses of self-interested managers. (266 words)

Key Words: Budgeting, forecasting, forecast error, production, sales and operations planning

Data Availability: Data are the property of the research partner and may not be redistributed by the authors.
1. Introduction

Budgetary systems, including both the annual “master budget” and the periodic subsequent forecasts, play two primary roles within business organizations. First, the master budget plays a control role by providing cost and sales benchmarks against which managerial performance can be assessed, and second, budgets and updated forecasts play a planning and coordination role for organizational activities (Hansen and Van der Stede 2004; Libby and Lindsay 2010; Horngren et al. 2011; Henttu-Aho and Järvinen 2013). While the determinants and consequences of budget-based control practices are among the most widely studied topics in management accounting research (Covaleski et al. 2003), there is little accounting research examining the planning and coordination role of budgets, and even less research examining the role that forecasts play in the coordination of activities through time and across functional units (Selto and Widener 2001; Hansen et al. 2003; Hansen and Van der Stede 2004).

This void in the literature is surprising given that many scholars and practitioners alike have noted an important organizational tension; namely, the use of budgetary systems for control leads to “gaming” by managers which undermines the usefulness of those systems for planning and coordination (Bittlestone 2000; CIMA 2004; Cassar and Gibson 2008; Sivabalan et al. 2009). This void in the literature is also surprising given evidence that indicates (i) CFOs name the ability to forecast as their top “internal concern,” (ii) managers regard planning uses of budgetary systems as more important than control uses (Sivabalan et al. 2009), (iii) forecasts are supplanting the budget as the primary planning and coordination tool, especially in highly uncertain environments where the master budget quickly becomes obsolete (Bittlestone 2000; CIMA 2004; Vadasz and Lorain 2010; Hagel 2014; Sivabalan et al. 2009; Ekholm and Wallin 2011), and (iv) managers perceive shortcomings in both budgets and forecasts as planning and coordination tools. The purpose of this study is to examine the role of sales forecasts as the coordination mechanism between sales managers and production
managers, a process referred to as “sales and operations planning” (S&OP) (Oliva and Watson 2011). This coordination mechanism is relevant for almost all production firms and is, as we show in our study, vulnerable to misaligned incentives between agents that need to coordinate their efforts.

Because sales forecasts are a prediction of future demand they are inherently subject to error. We define forecast error as the absolute difference of the sales forecast from actual sales. An extensive body of operations research documents the negative consequences of sales forecast error in the form of production plan instability that results in significant costs associated with inventory handling, inventory obsolescence, labor overtime, increased materials costs, increased freight costs, increased record-keeping costs, quality failure costs, and lost sales. Operations researchers also provide analytic and simulation evidence on how to respond to sales forecast error through the use of inventory “buffer” stocks. In contrast, we focus on whether a change in the sales forecasting information environment can reduce forecast error and, hence, the need for those buffer stocks. The objectives of our study are twofold. First, we document how the disaggregation of sales forecast information affects forecast error. Second, and more importantly, we analyze how providers and users of this information react to this disaggregation, taking into account the organizational context of individual incentives, responsibilities, and self-interest.

Our research setting is a large agricultural chemical manufacturing organization. Our site is an ideal setting to analyze the role of sales forecasts in the S&OP process for at least three reasons. First, the industry is characterized by high volatility in customer demand ensuing from market (i.e., competitor), economic (i.e., commodity prices), and natural forces (e.g., weather patterns). As a result, sales forecasting is particularly challenging and sales forecast accuracy is often compromised. Because of the uncertainty, there is significant

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1 For reviews of this literature, see Aytug et al. (2005), Gunasekaran and Ngai (2005), Burgess et al. (2006), and Mula et al. (2006).
information asymmetry between sales managers and production managers, increasing the importance of having an effective forecasting system. Second, the industry has a complex production process and extensive and complex supply chain system where forecast accuracy is likely to have a significant impact on production plans and the associated supply chain costs. Third and of particular relevance to this study, during the period of study, our research site introduced into the S&OP process a sales forecast “contingency system” that allowed sales managers to disaggregate the sales forecast into two components: (i) an official sales forecast that reflected relatively more certain expected demand, and (ii) a separate report that provided the probability of a contingent demand “event” occurring and the expected volume impact of that event. This feature of the research setting allows us to examine the effects of sales forecast disaggregation on forecast error, inventory, and production decisions.

Our study proceeded in two stages. In the first stage of the study, we conducted interviews (19 field interviews at corporate headquarters with managers from various departments and 11 interviews with different managers at a local production site) to gain an understanding of the budgeting and forecasting process, including the incentives faced by the relevant decision-makers and the perception of the S&OP contingency system introduction. We draw on these interviews in interpreting our findings. In the second stage of our study, we collected from both the production plant and the corporate headquarters stock-keeping-unit (SKU) level data on sales forecast error, finished goods inventory levels, and various product attribute variables to be used as controls in our analysis.

The sales forecast “contingency system” introduced at our field site provided a formal mechanism whereby sales managers could log contingencies in future product demand, such as a potential outbreak of a late season pest or a possible weather event, either of which, while low in probability, could have a significant effect on demand. Whereas in the pre-introduction period, sales managers had to make judgment calls about whether and when to include
potential events into the sales forecast, once the contingency system was in place, they had a means of communicating highly uncertain contingent demand “events” outside of the official forecast. The system allowed the sales managers to report important details regarding the source and timing of the event, the potential volume impact, and its probability of occurrence. From the point of view of the organization, the objective of the contingency system was to improve the accuracy of the official sales forecast and to facilitate better timing of production, the results of which were expected to be a reduction in finished goods inventories without an increase in production plan instability.

Consistent with the firm’s objective, we find that absolute sales forecast error declines in the post-introduction period with a favorable (i.e., negative) effect on finished goods inventory levels. However, we also hypothesize that self-interested sales managers have an incentive to positively bias the official forecast in order to ensure adequate inventory should the contingent demand event materialize. The contingency system provides increased opportunity to introduce positive bias through, for example, the selective logging of positive (but not negative) events. Accordingly, we predict and find that positive forecast bias increases following the introduction of the sales forecast contingency system, with an offsetting unfavorable (i.e., positive) effect on inventory levels.

We further predict and find a direct favorable (i.e., negative) effect of the contingency system introduction on finished goods inventory levels incremental to the indirect effects on inventory through changes in sales forecast error and bias. Importantly, the decline in finished goods inventory was achieved without a corresponding increase in production instability. This is in line with the contingency system facilitating a “postponement” strategy where the transformation of work-in-process inventory to finished goods inventory is delayed as long as possible to avoid costly production plan changes, addressing motives of production managers. We conclude that while the introduction of the contingency forecast system had the net effect
of facilitating a reduction of inventory levels without a degradation in production stability, the benefit of the system was partially undermined by increased positive forecast bias on the part of self-interested sales managers.

This study makes several important contributions to both the accounting and operations literatures. The operations literature is replete with analytic and simulation studies of the effects of sales forecast error on inventory levels and production instability, most of which aim to identify previously unrecognized optimization opportunities (Boudreau et al. 2003). This research, however, provides a dearth of empirical evidence of these associations (Kerkkänen et al. 2009), resulting in a stream of research that is largely devoid of the organizational context within which decisions are actually made, including the incentives that decision-makers face and the quality of information at their disposal. We contribute to this literature by examining the S&OP process within the organizational context. Specifically, we study a change in the information environment within our organization and we test theoretically-supported predictions regarding the responses of self-interested sales managers. We provide empirical evidence regarding the intended and unintended consequences of sales forecast disaggregation.

We also contribute directly to the accounting literature. The accounting budgeting literature has dealt at great length with the gaming behavior of managers working under budget-based incentive contracts (e.g., Merchant 1985; Young 1985; Chow et al. 1988; Waller 1988; Chow et al., 1994; Dunk 1989, 1993; Fisher et al., 2002; Shields and Shields 1998). The focus of this literature is on the misalignment of incentives of subordinate managers (i.e., agents) opportunistically participating in the budgeting process at the detriment of the firm (i.e., the principal). But there are agency costs at every level of the organization associated with managers who must obtain the cooperation of each other (Jensen and Meckling 1976). Jensen and Meckling (1976, p. 309) note,
“… the analysis of these more general organizational issues is even more difficult than that of the ‘ownership and control’ issue because the nature of the contractual obligations and rights of the parties are much more varied and generally not as well specified in explicit contractual arrangements.”

Our study examines the misalignment of incentives between two groups of agents, sales managers and production managers. Interestingly, whereas the accounting literature provides extensive evidence of the tendency of managers to generate pessimistic sales budgets (i.e., build budget “slack”) to affect budget-based incentives, we show that subsequent sales forecasts critical to coordination are actually optimistically biased. Our study thus speaks to the more general organizational issues that Jensen and Meckling (1976) identify but have largely been ignored in the accounting literature, and answers calls for more research of the largely undocumented consequences for the users of (potentially inaccurate and biased) budgeting and forecasting information (Jonsson 1998; Wacker and Lummus 2002; Hall 2010).

Lastly, our study provides rare and unique insights on the effects of sales forecast disaggregation that serves to provide transparency regarding sales demand uncertainties. Few studies have examined the judgment aspects of forecasts in an empirical setting (Fildes et al. 2009). We show that both intended and unintended effects emerge and provide insight into the magnitude of these effects in practice, a distinct advantage of field research over analytic and experimental research.

2. Research setting

AgroCo

Our research setting is AgroCo, a leader in the agricultural chemical industry, an industry characterized by high product and production process complexity and uncertain annual demand and product life cycles (uncertain time to market/complex patent structures). Demand uncertainty is endemic to this industry because demand for agricultural products—namely, herbicides, fungicides, and insecticides—varies based on weather, pests, and grower
plantings driven by – among other things - commodity prices. Moreover, the nature of the production processes (i.e., the management of complex “active ingredients” with lengthy formulation lead times) makes production and supply chain planning particularly challenging. Thus, the agricultural chemical industry in which AgroCo operates is ideal for examining the interplay between sales forecasts and production planning.

*The “S&OP contingency system” at AgroCo*

During the period of study, our research site introduced a forecast system innovation, the so-called “S&OP contingency system,” that disaggregated the sales forecast based on the level of *ex ante* uncertainty. The system enriches the sales forecast information environment by providing a mechanism for sales managers to disaggregate the forecast into two components: (i) an official sales forecast that reflects relatively certain expected demand, and (ii) a separate report that provides information regarding highly uncertain contingent demand, including the probability of the contingent demand “event” occurring, the expected volume impact of that event, as well as the expected sign (positive or negative) of the effect on expected demand.

While the firm set guidelines on how to classify contingent demand events into three probability thresholds (30%, 60%, and 90%) based on the characteristics of the potential events, ultimately the estimated probability of occurrence for each identified contingent event is subjectively determined by the sales managers. Contingent demand (again, this can be either positive or negative) makes it into the official sales forecast (is “triggered”) at a threshold probability of 90% at which point it is fully incorporated into production plans. Contingent demand with a threshold probability of 60%, while not part of the official forecast and therefore not included in production plans, is nonetheless visible to production managers as an information item that allows them to take preliminary steps to plan for the potential change in demand. A typical step a production planner may take for a 60% positive event
would be to assess the availability of “active ingredients” that might be needed.

The firm’s stated purpose for the new “S&OP contingency system” is twofold. First, the firm intended to reduce required inventory buffer stocks by reducing the error in the official sales forecast that is acted upon by production planners. Second, the forecast disaggregation into the official forecast and the information items (i.e., the 60% contingent demand events) was to facilitate a production postponement strategy in which final, SKU-level production is delayed as long as possible. The system thus provides a natural experiment that allows us to examine the consequences of sales forecast disaggregation. We next provide a theoretical background of our expectations and formulate our hypotheses.

3. Theoretical background and hypotheses

In this study, we examine one organization’s information approach to addressing the problems associated with sales forecast error and the costs thereof. Instead of focusing on how best to respond to sales forecast error by optimizing inventory and production plans, the organization focused on how the information environment might be altered to make the sales forecast more accurate, and hence more useful, for production planning and inventory decisions. We exploit this natural experiment to examine how the manner in which expected demand is incorporated into the sales forecast affects the decision usefulness of those forecasts (c.f., Baiman and Demski 1980). Importantly, we also consider the context of the organizational environment and the implications that has for how self-interested sales managers will respond to the changing sales forecast system; that is, we also consider the decision control role of sales forecasts (c.f., Baiman and Demski 1980). Indeed, the preponderance of the operations research examining S&OP processes uses analytical or simulation methods (Pujawan and Smart 2012; Kerkkänen et al. 2009) to identify previously unrecognized optimization opportunities through inventory management and production strategies (Boudreau et al. 2003). As such, the S&OP process as historically studied in the
operations literature is viewed in a very mechanistic way, with little attention paid to the opportunistic behaviors of self-interested managers.

Determinants and consequences of sales forecast error

The operations literature establishes the inextricable link between a manufacturing organization’s sales function and its operations function via the S&OP process. The S&OP process involves the translation of information regarding expected demand, current work-in-process and finished goods inventories, and labor and material availability into viable production plans that provide for production on a timely basis (Bowersox et al. 2012). The annual static budget provides the initial sales forecast that serves as the performance benchmark for sales managers and forms the basis for the initial production, raw materials purchases, labor, and overhead budgets. As the budget year progresses, sales managers update sales forecasts at regular intervals—typically monthly or quarterly—to reflect the latest information available which, in turn, allows production managers to revise production plans and inventory levels. The sales forecasting system is, thus, at the heart of S&OP coordination.

The measure of forecast system effectiveness is how well the forecasts support the coordination of sales and operations with forecasts that are integrated, accurate, detailed, and timely (Oliva and Watson 2009; Bowersox et al. 2012). The objective is to “bring production through in the required quantity, of the required quality, at the required time, and at the most reasonable cost” (Younger 1930, p. iii, as quoted in Aytug et al. 2005).

Because sales forecasts are a prediction of future demand they are inherently subject to error. The statistical algorithms based on historical data (e.g., exponential smoothing) that are often used to generate a baseline sales forecast are imperfect predictors of future demand. Further, sales managers typically use their own judgments to adjust the baseline forecast to incorporate other factors expected to affect demand but not reflected in historical data, including observed and expected competitor actions, changing market conditions, and
anticipated customer responses to the organization’s promotion activities (Bowersox et al. 2012; Cassar and Gibson 2008; Fildes et al. 2009; Oliva and Watson 2009; Sivabalan et al. 2009). Despite their best efforts, sales managers have limited ability to perform the cognitively demanding process of incorporating numerous sources of demand information into a single, comprehensive sales forecast (Fildes et al. 2009). Forecast error thus derives both from imperfect statistical prediction models and from the bounded rationality of sales managers. We define forecast error as the absolute difference between forecasted and actual sales. Greater forecast error indicates larger deviation of the sales forecast from actual sales.

Prior operations research documents the significant costs of sales forecast error. One well-developed stream of operations research documents an association between sales forecast error and the instability of production planning (e.g., Blackburn et al. 1987; Aytug et al. 2005; Kadipasaoglu et al. 1995; Bai et al. 2002; Xie et al. 2003; Jeunet 2006; Kerkkänen et al. 2009; Pujawan and Smart 2012). Production instability is the “intensity of revisions or changes to the production schedule over time” (Pujawan and Smart 2012) and results in significant costs associated with inventory handling, inventory obsolescence, labor overtime, increased materials costs, increased freight costs, increased record-keeping costs, quality failure costs, and lost sales (Lee and Adam 1986; Inman and Gonsalvez 1997; Wacker and Lummus 2002; Kerkkänen et al. 2009; Pujawan and Smart 2012).

A second extensive stream of operations literature examines mechanisms to reduce the negative effects of sales forecast error on production stability (e.g., schedule freezes and lot-for-lot ordering, Blackburn et al. 1987). Of particular importance to this study is research that determines the optimal level of finished goods inventory “buffer stocks” to mitigate the effect of sales forecast error on production stability (e.g., Sridharan and LaForge 1989, 1990; Bai et al. 2002; Toktay and Wein 2001; Enns, S. T. 2002). In determining the optimal level of

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2 This is sometimes referred to as “production schedule nervousness” (c.f., Kadipasaoglu et al. 1995; Pujawan and Smart 2012).
inventory, the aforementioned costs of production instability are balanced against increased holding costs of the buffer stocks (Blackburn et al. 1987; Sridharan and LaForge 1990). This research shows that increased sales forecast error requires increased levels of inventory to buffer the negative effects on production stability. In this study, we investigate the information approach of an organization to improve the process of sales forecasting and production planning, thereby making the sales forecast more accurate, and hence more useful, for production planning and inventory decisions.

Sales forecast disaggregation

In a traditional sales forecasting system sales managers provide to production managers a single, aggregated sales forecast that reflects all expected future demand. On the one hand, an aggregate forecast reflects a more complete set of demand information. Aggregation has the benefit of allowing for negatively correlated sources of demand information to offset, thereby reducing overall variability in observed total demand (Arya and Glover 2014). On the other hand, aggregated forecasts result in a loss of information (Arya and Glover 2014) by obscuring the characteristics of the various components of demand. Some sources of expected demand are recurring over time with relative certainty as to the demand materializing and the expected quantities (i.e., low variance around an expected value). Recurring orders from current customers and seasonality effects are examples. Other sources of demand, however, are highly uncertain (i.e., high variance around an expected value) and more difficult to forecast, such as the outbreak of a late season pest or an unexpected weather event in our research setting. These sources of demand thus relate to contingent events that have a low, albeit nonzero, probability of materializing but may have large effects on demand volume. While an aggregate forecast obscures these differences, disaggregation of these two sources of information serves to enrich the information environment for the users of the forecast information system. Indeed, prior research in
financial accounting documents benefits to investors, analysts, and auditors of disaggregated management forecasts.\textsuperscript{3}

In addition to enriching the overall information environment for the users of the forecasted demand (i.e., the production managers), disaggregating the highly uncertain contingent demand from the official sales forecast will result in a more accurate official forecast for two reasons. First, the disaggregation removes demand that has a low probability of materializing. If the contingent demand omitted from the official forecast does materialize, forecast error will be greater than if the contingent demand had been included in the official forecast. However, the reason the contingent demand is disaggregated from the official forecast in the first place is that it is unlikely to occur. Hence, the official forecast will, on average, be more accurate when highly uncertain contingent demand is omitted.

Second, the aggregation of multiple demand sources into a single point estimate is a cognitively challenging task that likely results in greater error. Fildes et al. (2009) find that when forced to combine relatively certain information with uncertain information into a single forecast, forecasters fail to fully incorporate the uncertain information into an aggregate number, thereby reducing the accuracy of the aggregate forecast. Disaggregating the forecast into its components reduces the cognitive demands of the forecast judgment (Ravinder 1988; Henrion et al. 1993) and leads to more complete consideration of all available information (Chen et al. 2015). Indeed, prior laboratory experiment research documents improved forecast accuracy (Chen et al. 2015) and greater inter-rater reliability among forecasters (Arkes et al. 2009) for disaggregated forecasts as compared to aggregated forecasts. Because sales forecast disaggregation results in a reduction in cognitive load, we expect improved judgments of each

\textsuperscript{3} Studies document improved accuracy and reduced earnings fixation (Elliott et al. 2011; Esplin et al. 2014; Kelton and Murthy 2015) of investor judgments for investors who receive disaggregated financial information. Other research documents that firm provision of disaggregated earnings information leads to improvements in accuracy and reductions in dispersion and bid-ask spreads of analyst forecasts (e.g., Hunt et al. 2012; Lansford et al. 2013; Chen, Miao, and Shevlin 2015). In an auditing context, Libby and Brown (2013) find that disaggregation of income statement numbers reduces auditors’ tolerance for misstatement.
component of the sales forecast in our setting – the more certain demand in the official forecast, and the highly uncertain demand in the event reporting system. We therefore predict that the disaggregated official sales forecast, as compared to the aggregated forecast, will result in lower \textit{ex post} absolute sales forecast error, on average. Stated formally:

\textbf{H1a: Sales forecast disaggregation will be associated with lower absolute sales forecast error, on average.}

While hypothesis H1a makes a prediction regarding the intended effect of sales forecast disaggregation on absolute sales forecast error, we also consider the potential for an unintended effect of increased sales forecast bias; that is, an asymmetrical tendency toward positive, versus negative, sales forecast errors.

We assume that sales managers are incentivized to meet all demand and base our expectations regarding the tendency of sales managers to positively bias sales forecasts on Terwiesch et al. (2014).\footnote{Our field interviews confirmed our assumption that sales managers are particularly interested in meeting all demand and to avoid any forgone revenues.} Terwiesch et al. (2014) examine an inter-firm setting in which buyers provide forecasts in the form of non-binding “soft orders” to suppliers. As in a “prisoners dilemma”, the buyer and seller are collectively better off by cooperating (i.e., the buyer providing accurate forecasts and the seller producing to the forecast), but have individual incentives to exhibit non-cooperative behavior (i.e., the buyer inflates the forecast to protect against lost sales, and the supplier reduces production to protect against excess inventory). They show that buyers and sellers engage in a “tit-for-tat” strategy in which sellers punish buyers for volatile and inflated “soft orders” by allocating less production capacity to that buyer, and buyers respond by further inflating those non-binding soft orders.\footnote{This is one of the only studies of its kind in the operations literature that examines behavioral aspects of managers engaged in sales forecast and production decisions, and as noted, they do so in an inter-firm setting.}

Extending this to our intra-firm setting, sales managers have an incentive to inflate the official forecast to increase the probability that inventory will be available in the event that the
contingent demand materializes prior to being incorporated into the official forecast. This incentive exists irrespective of aggregation or disaggregation of the forecast. However, we argue that in the disaggregated system there is greater opportunity and incentive for sales managers to positively bias the forecast.

Abdel-Rahim et al. (2015) show experimentally that, as long as there is no discretion over classification, participants making a disaggregated forecast tend to report more truthfully to avoid the appearance of rent-seeking. However, they show that when classification discretion is present – as in our setting where sales managers choose whether to classify demand according to the probability thresholds provided – participants are more likely to forecast opportunistically. Henion et al. (1993) and Chen et al. (2015) provide consistent experimental evidence of greater positive forecast bias for disaggregated forecasts as compared to aggregated forecasts.

Sales managers in our setting have three mechanisms by which to increase positive bias in the official sales forecast. First, they misclassify some of the contingent demand into the official sales forecast, essentially “padding” the forecast with some portion of the highly uncertain demand. Second, sales managers can omit negative demand events from the contingency system, thereby allowing only those demand events that have upside potential to be “triggered.” Lastly, sales managers can provide more optimistic probability assessments for positive demand events as compared to negative demand events. The result will be an asymmetrical tendency toward the “triggering” (i.e., moving into the official forecast) of positive but not negative events. That disaggregated forecasts are judged to be more credible than aggregated ones by recipients of the information (Hirst and Koonce 2007) will increase the incentives for sales managers to engage in these opportunistic behaviors. Given the

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6 Sales forecast bias can also result from unintentional cognitive biases of sales managers (Kerkkänen et al. 2009). For example, sales managers may insufficiently consider current inventory when forecasting production needs, resulting in positively biased forecasts (Bloomfield and Kulp 2013).
increased opportunity and incentive to increase positive forecast bias that the new contingency system provides, we predict that sales forecast positive bias will be greater in the disaggregated sales forecasting system as compared to the aggregated forecasting system. Stated formally:

**H1b: Sales forecast disaggregation will be associated with higher sales forecast positive bias, on average.**

In sum, we predict sales forecast disaggregation will be associated with a decline in absolute sales forecast error, but an increase in sales forecast positive bias. Thus, while the *intent* of the disaggregated sales forecast system is for the official sales forecast to be disaggregated from the contingent expected demand, we expect the incentives of sales managers to lead them to undermine the system by introducing sales forecast positive bias.

Our next hypothesis formalizes our expectation of the effect of sales forecast disaggregation on inventory and is based on extensive prior operations research documenting the prevalent use of inventory buffer stocks as a means of mitigating the adverse production instability consequences of sales forecast error (c.f., Aytug et al. 2005; Gunasekaran and Ngai 2005; and Mula et al. 2006) . The general finding of this research is a positive association between absolute forecast error and finished goods inventory levels. We further expect greater inventory levels associated with positively biased sales forecasts provided by sales managers seeking to protect against lost sales. Stated formally:

**H2a: There is a positive association between absolute sales forecast error and finished goods inventory.**

**H2b: Positively biased sales forecasts are associated with higher levels of finished goods inventory relative to unbiased or negatively biased forecasts.**

H2a thus implies that sales forecast disaggregation will have an indirect favorable effect on finished goods inventory levels (i.e., inventory reduction) through the reduction in absolute sales forecast error predicted in H1a, and H2b predicts an indirect unfavorable effect on finished goods inventory levels (i.e., inventory increase) through the increase in sales forecast
positive bias predicted in H1b.

We also consider the potential for a direct association of sales forecast disaggregation on inventory levels over and above the indirect associations predicted by H1a, H1b, and H2. Based on prior operations literature focused on designing optimal production strategies in the presence of demand uncertainty, we predict that the introduction of disaggregated forecasts, by providing an enriched information environment for the production managers, will facilitate a production “postponement” strategy (e.g., van Hoek 2001; LeBlanc 2007; Garcia-Dastugue and Lambert 2007). Production postponement refers to the delay in transforming work-in-process inventory to SKU-level finished goods inventory as long as possible to allow for the resolution of uncertainty and has been shown to be effective in reducing production instability derived from forecast error (LeBlanc 2007; Boone et al. 2007; Garcia-Dastugue and Lambert 2007). Disaggregated sales forecasts facilitate a production postponement strategy by providing production managers the necessary information to accelerate finished goods production of the more certain and reliable portion of the official sales forecast, while delaying production of the highly uncertain contingent demand. We, thus make the following prediction:

**H3: Sales forecast disaggregation is associated with a reduction in finished goods inventory.**

Importantly, an effective production postponement strategy will result in lower finished goods inventory, *without an increase in production instability*. That is, a successful postponement strategy means that lower amounts of inventory buffer stocks are needed to achieve the same level of production stability. In other words, production plan changes will be less sensitive to inventory holding levels after the forecast disaggregation, resulting in a weakening of the negative association between finished goods inventory and production instability. Formally, we make the following prediction:

**H4: Sales forecast disaggregation is associated with a weaker negative association**
between finished goods inventory and production instability.

Figure 1 summarizes our hypotheses. Hypotheses related to the effects of sales forecast disaggregation on finished goods inventory, either indirectly through a change in absolute sales forecast error (H1a and H2a), or directly through an effective postponement strategy (H3 and H4) reflect the intended consequences of the disaggregated sales forecast system. By contrast, hypotheses related to the indirect effects of sales forecast disaggregation on finished goods inventory (H1b and H2b) through increased forecast bias reflect an unintended consequence of the system arising from the intentional and opportunistic actions of self-interested sales managers.

4. Field evidence of the S&OP process and data sources

Interview protocol

To obtain a detailed understanding of the impact of sales forecast error on operational performance as well as the role of the new contingency system, we conducted field interviews at AgroCo with managers from various corporate departments, such as Marketing, Forecasting and Supply Chain Planning, and Logistics. We conducted our field interviews in two series. In early 2011, we interviewed 19 managers at AgroCo who were familiar with the sales forecasting process, or had an active role in it, in order to get an overall understanding of the forecasting process and of the drivers of forecast error. From these discussions we developed the interview protocol for the production plant, where we sought to investigate the perspective of the production side, and analyze the role of forecast error in production scheduling. In late 2011, we conducted interviews with 11 managers from all relevant functional areas at AgroPlant, i.e., plant management, production engineering, plant finance, R&D and quality, asset planning, and vendor scheduling. The objective of the second interview series was to identify the impact of sales forecast error on the complete operation cycle of the plant (procurement – production – inventory).
Although we guided our interviews by a standardized set of questions, the interviews were primarily kept open-ended to allow the interviewees to provide their perspectives on the determinants and consequences of sales forecast error. The research team was alert not to ask any leading questions, using the interview protocol as guidance. The interviews were recorded and transcribed by a professional transcription firm. The interview transcripts were analyzed by multiple members of the research team to gain consensus over the most important insights, and our main conclusions were validated with follow-up interviews at the firm. The archival data were collected either on site following the respective interviews, or provided digitally at a later point in time. Following the interviews, we held phone meetings if clarifications about the data were necessary. In the following section we describe our main insights from our interviews regarding the determinants and consequences of sales forecast error.

Field evidence on the forecasting process

Our detailed field interviews revealed a sales budgeting and production planning process at AgroCo that is very complex and involves many different parties. The interviewees expressed opinions that there are considerable biases in both the annual budget and the monthly forecasts driven largely by incentives that the parties face. The S&OP system at AgroCo results in both a sales budget and a production plan, established at different points in time. Production plans for the upcoming budget (i.e., calendar) year are initially developed by the production units in July based on older long-term forecasts. In October annual sales budgets for each family of product (i.e., all products from a single active ingredient), without regard to specific product type or packaging, are proposed by each business unit representing a geographic marketing region with input from sales managers and finance managers. The sales budget is often not officially approved until January of the budget year once finance has reviewed prior year-end sales results. Although claimed to be a “top-down budget” from Headquarters, the described bottom-up sales budget is largely approved as submitted by the
sales managers. As a business unit marketing head states:

“The top-down budget from Headquarters is 95% or 90% — a number I provided them to begin with. ... There may be a few overviews, but it’s largely our number to begin with.”

The annual sales budget established in October is binding on the sales managers, serving as the primary basis for the sales force incentive plan. More specifically, sales and marketing (i.e., district managers and salespersons) incentive bonuses are based on the achievement of the business unit sales budget (50%), the corporate sales budget (25%) and a subjective performance assessment of a qualitative nature. Although forecast error is a designated input into the subjective assessment, interviewees indicated that its importance to the overall bonus is low.

Once the sales budget is approved, ownership is transferred back to the business units (BUs). Usually, the first revisions to the budget in the form of updated forecasts begin in January and subsequently take place on a monthly basis following a standardized protocol.

The demand volatility causing the forecast revisions is claimed to be driven by market (i.e., competitor), economic (i.e., commodity prices), and natural forces (e.g., weather patterns). Although these factors can drive forecasts to be revised in either direction, the interviews suggest that the BUs have an incentive to over-forecast rather than under-forecast throughout the year to avoid lost sales and be able to react to supply failures of competitors. One marketing manager remarks:

“...given the seasonal nature of our business, we find that if we under forecast, the likelihood of us having supply gets to be difficult. And by that I’m saying if I were to raise my forecast substantially 30 days before I needed product, there’s a pretty good chance I won’t receive all of what I had for demand.”

The interviews also revealed that AgroCo benefits from sales taken from (smaller) competitors that are not able to react to demand swings caused by weather conditions or revised grower planting choices. This implies that in order to be ready to react to these contingencies, forecasts are more likely to be positively biased.
Field evidence on the impact of the sales forecast contingency system

The interviews at our field site provided us with rich information on the contingency system innovation that was intended to increase the transparency of highly uncertain contingent demand; that is, non-trivial environmental or market (i.e., customer or competitor) demand events for which there was a very low, albeit nonzero, probability of occurring. The system allows the sales managers to add a so-called contingency “event” in a separate reporting structure outside of the official forecast but visible to production planners. In essence, the system provides for a disaggregation of the portion of demand associated with highly uncertain contingent events from the overall sales forecast, resulting in an official sales forecast intended to capture only the relatively more certain sources of demand. Each event entry into the system communicates an expected demand quantity effect (either up or down), the reason for the potential demand effect, and the probability of occurrence. One of the brand managers explained:

“We generate the events and work with our supply chain planners to make sure that everybody is aware of what the event is and when it should be triggered. And generally they’re market driven. Could be a weather event. It could be an acreage event. It could be a pest event. In the case of soybeans, soybean aphid is a pest that comes periodically. But when it comes, it’s a huge upside and we never know if it’s going to come until it’s there.... So we use an event structure to allow us to flag those”

Once an event is assessed at 90% probability of occurring, the event is added to the official forecast. Whereas this new system allows for better communication of demand contingencies, it also introduces additional opportunities for gaming on the part of the sales managers. Indeed, positive events are much more likely to be “triggered” (i.e., entered into the forecast) than are negative events, reflecting an asymmetrical preference on the part of sales managers to avoid stockouts more than to avoid excessive production, especially for higher margin products. As stated by one of the finance managers:

“Well, considering the lost sales opportunity for products with a low margin, yeah you don’t want a bunch of that sitting around. But some of these seed care products have [a very high] margin. You’re crazy to miss a sales opportunity because you didn’t
want to have a little bit of carrying cost for that inventory. We’d be better off carrying a little bit of inventory. We are scrambling right now because we have this huge opportunity in cotton, and that’s a huge gross margin product, but we didn’t forecast for it because this is truly an event that was unforeseen.”

And in a competitive setting when a competitor cannot produce on time:

“So we have the opportunity to fill that gap. And it’s a huge profit margin and we are making our supply chain go through hoops. But it’s potentially a $XX million upside or $XX million upside. ... We may hold that market share next year, up to 90% of it. So we’d be fools not to try to get it.”

These interviews thus show that the system can help to react quicker to demand volatility.

5. Data Sources and Variable Descriptions

We use monthly data on product level for the period of 2006-2010 to examine the effect of the S&OP contingency system introduction, i.e., the forecast disaggregation, on forecast error and inventory. Our sample comprises 2,300 monthly observations of 80 unique products. In order to use a consistent sample across all analyses, we restrict the sample to those observations for which we have data on all variables, leaving us with 1,839 product-month observations of 70 unique products. Data were collected from two major sources. We obtained sales (related) data from the corporate sales department at AgroCo, including sales forecast error, sales price, and supply chain complexity. Production data were locally obtained at AgroPlant. These data include detailed information on production decisions (e.g., quantities, sequencing, production changes). We limit our analysis to the products of two specific production lines within AgroPlant for which data about the production process had been thoroughly and consistently documented over our sample period. Below we define the variables used in our analysis and the sources for data collection.

The contingency system implementation

The sales forecasting contingency system was introduced in the end of 2007 and comprehensively implemented in January 2008. We create an indicator variable for the pre- and post-introduction period. We label POST as 1 in the years 2008-2010 after the
introduction, and 0 otherwise.

Sales forecast error variables

The sales data were collected from AgroCo’s global forecast reporting tool, which produces monthly sales forecast error information on product level as the major KPI. Forecast error (FCSTERROR) is defined as the absolute deviation of the actual sales (AS) from the forecasted sales (FS), three months out, i.e., \( Error = |AS-FS|/AS \).

Forecast bias is signed forecast error, with positive forecast error indicating a forecast greater than actual sales (i.e., positive bias) and negative forecast error indicating a forecast lower than actual sales (i.e., negative bias). We create two variables to distinguish between positive and negative sales forecast error: \( D_{POS} (D_{NEG}) \) is set equal to one for observations indicating a positive (negative) forecast error, and zero otherwise.

Production variables

Forward coverage (FORWARD) is the number of months’ sales (based on actual subsequent sales) in finished goods (i.e., SKU-level) inventory at the end of the month prior to the month of production.

Production instability is captured by changes in the production plan, computed by subtracting Planned Production (PP) in units from Actual Production (AP), i.e.,

\[ PROD\_CHANGE = AP - PP. \]

To control for scale effects and determine the effect of percentage deviations of actual production from forecasted production, we compute \( \ln \) \( PROD\_CHANGE \) as the absolute logarithmic deviation of the AP from PP, i.e., \( \ln \)

\[ PROD\_CHANGE = |(\log AP + 1) - (\log FP + 1)|. \]

4.4 Control variables

Given that our main independent variable \( POST \) is measured in terms of time, we control for time trend in three different ways. First, we control for the product-specific time

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7 Given the seasonality of the business and the resulting non-trivial number of observations with zero forecasted and/or actual production, we add one prior to computing the logarithms.
trend, starting with 1 in the month of product introduction (TREND). We also control for the fact that some products already existed at the beginning of the sample period (EXISTING), and allow the effect of trend to vary for these products (EXISTING * TREND). Second, we control for the monthly Producer Price Index (PPI) as reported by the United Stated Department of Labor, which measures the average change over time in the selling prices received by domestic producers for their output. Third, we control for seasonality by including indicator variables for months.

We control for variables that are likely to capture sales manager incentives to bias forecasts. QUANTITY is the budgeted sales quantity in physical units, expressed in liters. SALES VALUE is the sales price per unit of measurement (e.g., liters, gallons) multiplied by the individual product pack size (e.g., 100 liters, 2.5 gallons). Gross margin percentage (GMPCT) is calculated as the ratio of gross margin per unit (i.e., sales price minus standard costs) and sales price per unit. These three variables, QUANTITY, SALES VALUE, and GMPCT, reflect differences in product volume and profitability that may provide incentives to positively bias forecasts to ensure adequate inventory.

We also control for a number of additional variables that may affect forecast error and/or bias. First, we control for forecasting attributes of the product “active ingredient” (AI). Each product consists of one key component, called the lead AI, that multiple products share. AIs differ on a number of dimensions that make their derivative products more complex from a supply chain planning perspective, including the scarcity of the AI and the number of products derived from the AI. We control for four dimensions of AI complexity as measured by the firm on a scale of 0-10. AL_LIFECYCLE captures the lifecycle phase for a given AI’s product portfolio. AIs with new products in their portfolio yield the highest scores on this variable; AIs with mature products yield low scores. Because forecasting is more difficult during the product introduction phase, we expect forecast error to be higher for higher values
of \textit{AI\_LIFECYCLE}. Two complexity dimensions that capture competition for AI resources may give rise to incentives to bias sales forecasts in order to ensure adequate inventory. \textit{AI\_PRODUCTS} captures the number of products that share a certain AI. \textit{AI\_ALLOCATION} indicates the degree to which the AI is a scarce resource that needs to be allocated to the products sharing the AI (high scores), or freely available on the market (low values). Higher values of \textit{AI\_LIFECYCLE}, \textit{AI\_PRODUCTS}, and \textit{AI\_ALLOCATION} indicate greater complexity. Lastly, \textit{AI\_FCASTIBILITY}, is the firm’s overall assessment of the ease of forecasting AI demand, with higher values indicating lower complexity and greater ease of forecasting. Lastly, we control for whether or not the product is exported with \textit{EXPORT}, an indicator variable that equals 1 if the product is sold outside the US, and 0 otherwise. See Appendix for variable definitions.

6. Empirical Results

Descriptive statistics and univariate results

Table 1 provides descriptive statistics for the variables used in the empirical analysis (Panel A), as well as for the pre- and post-introduction period separately (Panel B). In Panels C and D, we provide descriptive statistics for nonzero values of \textit{FCSTERROR}, separated into positive and negative errors.

On average, the 3-month forecast error (\textit{FCSTERROR}) is rather high (2.007, Panel A). Overall forecast error increases from 1.75 to 2.10 (p<0.01) after the introduction of the S&OP contingency system. For the entire sample period 48.8\% of the forecasts are positively biased (with a mean of 3.817), while only 21.8\% of forecasts are negatively biased (with a mean of 0.657) (Panel C). Thus, the incidence of negative versus positive bias is not random as would be expected if only random error were at play. Interestingly, while the percentage of forecasts that are positively biased does not change with the system introduction (Panel B), consistent with H1b the mean magnitude of positive bias increases from 3.216 to 4.025 (p<0.01) after
the introduction of the sales forecast contingency system (Panel D). The incidence of negative forecast errors decreases from 28.1 percent to 19.5 percent after the system introduction (p<0.01) (Panel B). However, there is no change in the mean magnitude of negative errors (Panel D). Note, however, that there are numerous differences between the pre- and post-system descriptive statistics for many of the product attribute control variables that are expected to affect the direction and magnitude of forecast errors, suggesting inferences from univariate statistics may be misleading. In untabulated analysis using a multinomial logistic regression to model the incidences of negative, zero, and positive forecast errors, we find no incremental likelihood of a positive versus negative forecast error after the system introduction.

Lastly, our measure of production instability, PROD_CHANGE, does not change following the system introduction, and in contrast to H3, there also is no statistically significant decline in inventory forward coverage, FORWARD (Panel B). Again, however, these univariate tests do not control for changing product attributes. We now turn to multivariate tests of our hypotheses that allow us to control for these other factors.

**INSERT TABLE 1**

*The effect of sales forecast disaggregation on absolute sales forecast error and sales forecast positive bias (H1a and H1b)*

Hypotheses H1a and H1b examine the effect of sales forecast disaggregation on absolute sales forecast errors and sales forecast positive bias, controlling for changing product characteristics and time trends. We first estimate a reference model of FCSTERror against all the control variables. We estimate a tobit regression model because of the preponderance of zero observations in the dependent variable, FCSTERror, and cluster standard errors by product. The results are presented in Table 2, Model 1 and show that absolute forecast error increases over a product’s lifetime as indicated by the positive coefficient on TREND (p<0.01,
two-tailed), is higher for products with larger sales volume (QUANTITY, p<0.01, two-tailed), for products using AIs that are on allocation (AL_ALLOCATION, p<0.01, two-tailed), and is lower for high margin products (GMPCT, p<0.01, two-tailed).

Hypothesis H1a predicts a negative effect of forecast disaggregation on absolute sales forecast error which we test by estimating the following empirical model:

\[ FCSTERROR = \theta_0 + \theta_1 POST + <controls> \] (1)

The coefficient on POST, \( \theta_1 \), is expected to be negative. Results of the estimation of equation (1) are reported in Table 2, Model 2.

**INSERT TABLE 2**

Consistent with H1a, we find that absolute sales forecast error is lower after the forecast disaggregation as indicated by a negative coefficient on POST in Model 2 (coefficient of -0.860, p<0.10, one-tailed). This result, while only marginally significant, suggests that forecast accuracy improves for the disaggregated forecast, as compared to the aggregated forecast.

While H1a predicts that absolute forecast error will decline due to lower uncertainty of demand being forecasted, H1b predicts an increase in sales forecast positive bias following the introduction of the disaggregated forecast system. We test this hypothesis with the estimation of the following model:

\[ FCSTERROR = \theta_0 + \theta_1 POST + \theta_2 D_POS + \theta_3 D_POS \times POST + <controls> \] (2)

With this model specification, the coefficient on POST, \( \theta_1 \), is interpreted as the average change in magnitude of non-positive forecast errors, while the sum of the coefficients on \( POST, \theta_1 \), and \( D_POS \times POST, \theta_3 \), captures the change in magnitude of positive forecast errors. Hypothesis H1b predicts \( \theta_1 + \theta_3 > 0 \) (positive bias is larger). We again estimate this equation with a tobit regression model and cluster standard errors by product. The results of the estimation of equation (2) are presented in Table 2, Model 3.
Consistent with H1b the sum of the coefficients on $D_{POS}$ and $D_{POS} \ast POST$ is positive and significant ($-1.267 + 2.118 = 0.851$, $p < 0.10$, two-tailed), indicating that sales forecast positive bias is larger in magnitude following the system introduction. Note that we control for a potential trend in sales forecast positive bias to rule out the possibility that our finding in support of H1b merely reflects a trend in bias throughout the sample period. Specifically, we include an interaction term $D_{POS} \ast TREND$. The negative coefficient on this variable indicates that sales forecast positive bias is actually trending downward. Our finding of an increase in positive bias is incremental to this overall downward trend.

Recall that univariate tests indicate no change in the magnitude of negative forecast errors (Table 2, Panel B). To verify this, we re-estimate equation (4) substituting $D_{NEG}$ for $D_{POS}$. Results are presented in Table 2, Model 4. Consistent with univariate results reported in Table 2, Panel D, these multivariate results show that there is no change in the magnitude of negative forecast error from pre- to post-introduction of the disaggregated forecast system. Thus, the significant increase in the magnitude of positive forecast errors we document as support for H1b is not offset by a corresponding increase in the magnitude of negative forecast errors.

In our development of hypothesis H1b, we describe three mechanisms by which sales managers can increase positive bias in the official sales forecast. They can (i) “pad” the official forecast with some portion of what is actually contingent demand (i.e., miscategorize the demand), (ii) omit negative events from the contingency system, and (iii) provide more optimistic probability assessments for positive demand events as compared to negative demand events, leading to an increased rate of positive event “triggering” as compared to negative events. In untabulated analysis, we find evidence consistent with (ii) above in that 80% of all filed events are positive demand events. Further, while 43% of the positive events are triggered (reach the 90% probability level), only 19% of negative events are triggered.
This is consistent with (iii) above. This evidence, along with the multivariate results reported in Table 3, provide support for both H1a and H1b. The introduction of the contingency system resulted in a favorable decrease in absolute sales forecast error but an unfavorable increase in sales forecast positive bias.

Direct and indirect effects of sales forecast disaggregation on inventory (H2 and H3)

Hypotheses H2a predicts that absolute sales forecast error is positively associated with finished goods inventory levels. Hypotheses H2b predicts that positively biased forecasts will have an incremental positive association with finished goods inventory levels. Hypothesis H3 further predicts an incremental direct effect of sales forecast disaggregation on finished goods inventory levels reflective of a production postponement strategy. To test H2a, H2b, and H3, we estimate the following equation:

\[ \text{FORWARD} = \theta_0 + \theta_1 \text{FCSTERRO}R + \theta_2 D\_POS + \theta_3 \text{POST} + <\text{controls}> \]  \hspace{1cm} (3)

Hypothesis H2a predicts \( \theta_1 > 0 \), H2b predicts \( \theta_2 > 0 \), and H3 predicts \( \theta_3 < 0 \). The model is again estimated with a tobit estimation with standard errors clustered by product. Results of the estimation of (3) are presented in Table 3, Model 1.

INSERT TABLE 3

Consistent with H2a, the coefficient on FCSTERRO is positive and highly significant (coefficient of 0.182, p<0.01, one-tailed), indicating that higher absolute forecast error is, indeed, associated with higher inventory levels. The coefficient on D_POS is also positive and highly significant (coefficient of 2.120, p<0.01, one-tailed), indicating that positively biased forecasts are associated with higher inventory levels, on average. Taken together with evidence reported in Table 2, we conclude that the system introduction had a favorable effect on inventory (i.e., a decline in inventory) via the decline in absolute forecast error (H1a and H2a), but an offsetting unfavorable effect on inventory (i.e., an increase in inventory) via the increase in sales forecast positive bias (H1b and H2b).
Hypothesis H3 predicts a direct negative effect of the introduction of the disaggregated forecast system on inventory levels, incremental to the indirect effects documented above. Consistent with hypothesis H3, we find a significant negative coefficient on POST in Table 3, Model 1 (coefficient of -3.732, p<0.05, one-tailed). This is indicative of the contingency system facilitating the organization’s implementation of a production postponement strategy whereby final production of SKU-level product is delayed as long as possible to allow time for uncertainty to resolve.

Sales forecast disaggregation and production instability (H4)

A successful production postponement strategy achieves lower inventory levels without a corresponding increase in production instability. Hypothesis H4 predicts that the negative relation between inventory and production changes (i.e., the inventory buffering effect) will weaken after the system introduction. That is, that POST will moderate the relation between FORWARD and PROD_CHANGES. We test this hypothesis by estimating the following model:

\[
\text{PROD\_CHANGE} = \theta_0 + \theta_1 \text{FCSTERROR} + \theta_2 D\_POS + \theta_3 \text{POST} + \theta_4 \text{FORWARD} + \theta_5 \text{FORWARD X POST} + \text{<controls>} \quad (4)
\]

Hypothesis H4 predicts a positive coefficient \(\theta_5\). The results of the tobit estimation of equation (4) are presented in Table 3, Model 2. Consistent with prior operations research, there is a statistically significant negative coefficient on FORWARD (coefficient of -0.393, p<0.01, two-tailed) reflective of the buffering role that inventory plays. That is, higher inventory levels serve to mitigate the negative effects of forecast error on production instability. We find no association between either FCSTERROR or D_POS and PROD_CHANGES in this model, suggesting that inventory buffer stocks fully absorb the adverse effects of forecast error.

Turning to the hypothesis, we find that, consistent with H4, the coefficient on the FORWARD X POST interaction term is positive and marginally significant (coefficient of
0.184, p<0.10, one-tailed). The sum of the coefficients on FORWARD and FORWARD X POST remains negative (p<0.01); that is, inventory plays a buffering role throughout the sample period. However, the coefficient on the interaction term indicates that the magnitude of the effect declines by half (i.e., 0.184 is about half of 0.393). Thus, the disaggregated sales forecasting system resulted in lower finished goods inventory levels (i.e., H3), which was not associated with the same degree of increased production stability as would have been observed prior to the system introduction.

A postponement strategy delays the scheduling of finished goods production. The result is essentially a shift in average inventory levels from finished goods inventory to work-in-process inventory. To provide further evidence in support of our conclusion, in an untabulated analysis conducted at the plant level we find that the ratio of finished goods to work-in-process inventory decreases in the post-introduction period as compared to the pre-introduction period, indicating a shift from finished goods to work-in-process inventory. Taken together, the results supporting H4 along with the evidence regarding the shift in inventory are consistent with the contingency system providing for better timing of production through a production postponement strategy. A graphical summary of the results presented in Table 2 and 3 is presented in Figure 2.

7. Conclusion

In this study, we use field and archival methods to examine the sales and operations planning (S&OP) system within a large manufacturing organization. While the operations literature is replete with analytic and simulation studies of S&OP systems, this research fails to account for the role that incentives, biases, and organizational dynamics play in the S&OP process. Based on 30 field interviews with managers from a large agro-chemical firm, we augment our empirical analysis with an understanding of the process of sales forecasting and production planning at our research site.
Our study adds to the accounting literature and combines insights from the accounting and the operations research literature. While the operations research literature typically focuses on statistical demand models as a means of generating accurate forecasts, the accounting literature has dealt at great length with budgeting and the gaming behavior of opportunistically acting managers using their informational advantages to serve their own benefits. There is to our knowledge no study that examines the effect of gaming behavior by sales managers making sales forecasts, and how potentially biased budget and forecast information is incorporated into real decisions made by the users of this information, i.e., the inventory and production decisions of production managers. Whereas the operations research literature tends to ignore the possibility of gaming behavior in forecasting and planning, the accounting literature emphasizes its universal existence, but has so far not explored its consequences on operational decisions. Our study thus adds to the literature by quantifying the impact of sales forecast accuracy on inventory and production decisions.

We document that sales forecast disaggregation served to improve operational performance in the form of lower inventory directly through a production postponement strategy, and indirectly through decreased absolute sales forecast error. However, it also had unintended consequences for the firm. In particular, we find an (for the designers of the system) unexpected increase in sales forecast positive bias following the system introduction. This resulted in higher inventory levels, offsetting the reduction in inventory levels attained as a result of the better information quality of forecasts (i.e., lower absolute error). Thus, while the forecast disaggregation indeed increased the information quality of forecasts, on average, the benefits of better information quality were undermined by the increase in forecast bias of self-interested sales managers. Our results provide important evidence regarding the inextricable interactions between the planning use and the control use of accounting information within the organizational context.
Our study is subject to several limitations. First, we do not have detailed information on the incentive system and compensation formulas for individual sales managers and are unable to include direct measures of incentives in our analysis of sales forecast accuracy and bias. Nevertheless, we derive insights on the incentive system based on our field interviews and use these insights to facilitate our understanding and interpretation of our findings.

Further, our study is based on one firm which limits the generalizability of the specific findings related to effect magnitudes. However, the field insights related to a common form of incentivizing sales managers (i.e., sales bonus paid for beating budget targets) and the nature of the response of production managers likely generalize to other settings, in particular those with volatile demand and uncertainty and information asymmetry between sales and production managers. Demand uncertainty and volatility is common to many industries (Fisher et al., 1994), including high-tech semiconductor and consumer electronics industries and the pharmaceutical industry (Wu et al., 2005). In such settings, information asymmetry between sales departments and production departments are relatively high as sales managers are closer to the market and production departments cannot rely on historic data in their planning. Our findings thus generalize to many settings and provide insight into how the dynamics between sales and production managers manifest in organizational decision-making.
References


Figure 1
Hypothesized Relations

Figure 2
Summary of Results
Table 1
Descriptive Statistics

Panel A: Full Sample (N = 1,839)

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<th>Max</th>
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Panel B: Pre- versus Post-introduction Period

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<td>0.500</td>
</tr>
<tr>
<td>D_NEG</td>
<td>0.281</td>
<td>0.450</td>
</tr>
<tr>
<td>FORWARD</td>
<td>7.678</td>
<td>7.520</td>
</tr>
<tr>
<td>PROD_CHANGE</td>
<td>0.873</td>
<td>0.267</td>
</tr>
<tr>
<td>TREND</td>
<td>11.442</td>
<td>6.567</td>
</tr>
<tr>
<td>EXISTING</td>
<td>0.759</td>
<td>0.428</td>
</tr>
<tr>
<td>PPI</td>
<td>164.577</td>
<td>4.065</td>
</tr>
<tr>
<td>SALES VALUE</td>
<td>[omitted for confidentiality]</td>
<td>[omitted]</td>
</tr>
<tr>
<td>QUANTITY (1,000s)</td>
<td>[omitted for confidentiality]</td>
<td>[omitted]</td>
</tr>
<tr>
<td>GMPCPT</td>
<td>[omitted for confidentiality]</td>
<td>[omitted]</td>
</tr>
<tr>
<td>EXPORT</td>
<td>0.023</td>
<td>0.150</td>
</tr>
<tr>
<td>AI_LIFECYCLE</td>
<td>7.635</td>
<td>2.935</td>
</tr>
<tr>
<td>AI_PRODUCTS</td>
<td>6.516</td>
<td>1.144</td>
</tr>
<tr>
<td>AI_ALLOCATION</td>
<td>7.044</td>
<td>3.775</td>
</tr>
<tr>
<td>AI_FCASTIBILITY</td>
<td>4.224</td>
<td>3.947</td>
</tr>
</tbody>
</table>

*** p<0.01, ** p<0.05
### Panel C: Non-zero forecast errors

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Median</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>FCSTERROR (positive)</td>
<td>898</td>
<td>3.817</td>
<td>4.037</td>
<td>0.002</td>
<td>1.977</td>
<td>12.674</td>
</tr>
<tr>
<td>FCSTERROR (negative)</td>
<td>400</td>
<td>0.657</td>
<td>0.355</td>
<td>0.001</td>
<td>0.746</td>
<td>1</td>
</tr>
</tbody>
</table>

### Panel D: Non-zero forecast errors, Pre- versus Post-introduction Period

<table>
<thead>
<tr>
<th>Variable</th>
<th>Pre-introduction Period (POST = 0)</th>
<th>Post-introduction Period (POST = 1)</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>SD</td>
<td>Mean</td>
</tr>
<tr>
<td>FCSTERROR (positive)</td>
<td>N = 231</td>
<td>3.216</td>
<td>3.584</td>
</tr>
<tr>
<td></td>
<td>N = 134</td>
<td>0.675</td>
<td>0.342</td>
</tr>
</tbody>
</table>
Table 2
Test of Hypotheses H1a and H1b

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Model 1</th>
<th>Model 2</th>
<th>Model 3</th>
<th>Model 4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FCSTERROR</td>
<td>Pred. sign</td>
<td>FCSTERROR</td>
<td>Pred. sign</td>
</tr>
<tr>
<td>Constant</td>
<td>5.881</td>
<td>1.240</td>
<td>1.811</td>
<td>1.565</td>
</tr>
<tr>
<td>POST</td>
<td>-0.860*</td>
<td>(-)</td>
<td>-1.267**</td>
<td>-0.932*</td>
</tr>
<tr>
<td>$D_{POS}$</td>
<td>(+)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D_{NEG} \ast POST$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$D_{NEG}$</td>
<td>(+)</td>
<td>4.564***</td>
<td></td>
<td>0.115</td>
</tr>
<tr>
<td>$D_{NEG} \ast POST$</td>
<td>(?)</td>
<td></td>
<td></td>
<td>0.419</td>
</tr>
</tbody>
</table>

**Controls**

- $TREND$: 0.069*** 0.073*** 0.053*** 0.082***
- $EXISTING$: -0.047 -0.438 0.157 -0.441
- $EXISTING \ast TREND$: -0.031 -0.024 -0.016 -0.024
- $D_{POS} \ast TREND$: -0.031**
- $D_{NEG} \ast TREND$: -0.040**
- $PPI$: -0.031 -0.001 -0.018 -0.003
- $SALESVALUE$: -1.368 -1.242 -0.430 -1.249
- $QUANTITY$: 0.002*** 0.002*** -0.000 0.002***
- $GMPC$: -0.156** -0.150** -0.094*** -0.150**
- $EXPORT$: 0.456 0.494 0.733 0.483
- $AL_{PRODUCTS}$: -0.347** -0.341** -0.128 -0.334**
- $AL_{ALLOCATION}$: 0.122** 0.117** 0.012 0.118**
- $AL_{LIFECYCLE}$: 0.054 0.054 -0.023 0.045
- $AL_{FCASTIBILITY}$: -0.024 -0.025 0.042 -0.022
- $M2$: 0.884** 1.096** 0.532 1.039**
- $M3$: 1.625*** 1.821*** 0.406 1.723***
- $M4$: 1.182*** 1.349*** -0.092 1.250***
- $M5$: 1.953*** 2.093*** 1.103*** 1.975***
- $M6$: 1.181** 1.265** 0.727* 1.185**
- $M7$: 0.040 0.128 0.094 0.060
- $M8$: -0.082 -0.018 0.388 0.000
- $M9$: 0.084 0.131 0.361 0.112
- $M10$: 0.312 0.349 0.460 0.275
- $M11$: -0.239 -0.230 -0.179 -0.320

Observations 1,839 1,839 1,839 1,839
Pseudo R-squared 0.020 0.020 0.116 0.021
N-Left-censored 541 541 541 541
N-Clusters 70 70 70 70

*** p<0.01, ** p<0.05, * p<0.10. Indicated p-values are one-tailed for coefficients with predicted signs (i.e., ‘(+’) or ‘(-)’) and two-tailed otherwise.
<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>Pred. sign</th>
<th>Model 1</th>
<th>Pred. sign</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FORWARD</td>
<td></td>
<td>PROD_</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>-14.988</td>
<td>-54.739***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FCSTERERROR</td>
<td>H2a (+)</td>
<td>0.182***</td>
<td>-0.074</td>
<td></td>
</tr>
<tr>
<td>D_POS</td>
<td>H2b (+)</td>
<td>2.120***</td>
<td>1.253</td>
<td></td>
</tr>
<tr>
<td>POST</td>
<td>H3 (-)</td>
<td>-3.732**</td>
<td>-2.571*</td>
<td></td>
</tr>
<tr>
<td>FORWARD</td>
<td>(-)</td>
<td>-0.393***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>FORWARD * POST</td>
<td>H4 (+)</td>
<td>0.184*</td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Controls</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TREND</td>
<td>0.188***</td>
<td>-0.030</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXISTING</td>
<td>-0.831</td>
<td>2.426</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXISTING * TREND</td>
<td>-0.055</td>
<td>-0.010</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PPI</td>
<td>0.095</td>
<td>0.281***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>SALESVALUE</td>
<td>-3.803</td>
<td>2.621</td>
<td></td>
<td></td>
</tr>
<tr>
<td>QUANTITY</td>
<td>-0.003***</td>
<td>0.005***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>GMPCT</td>
<td>-0.610***</td>
<td>-0.360***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>EXPORT</td>
<td>-6.594***</td>
<td>-1.335</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AL_PRODUCTS</td>
<td>0.864</td>
<td>0.041</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AL_ALLOCATION</td>
<td>0.076</td>
<td>0.083</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AI_LIFECYCLE</td>
<td>-0.154</td>
<td>0.021</td>
<td></td>
<td></td>
</tr>
<tr>
<td>AI_FCASTIBILITY</td>
<td>0.311*</td>
<td>0.162</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M2</td>
<td>-0.189</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>M3</td>
<td>-1.952**</td>
<td>-0.381</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M4</td>
<td>-1.154</td>
<td>-4.341***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M5</td>
<td>-1.136</td>
<td>-1.325</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M6</td>
<td>-2.103**</td>
<td>-0.623</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M7</td>
<td>-1.838***</td>
<td>-2.605**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M8</td>
<td>-0.772</td>
<td>0.356</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M9</td>
<td>-0.767</td>
<td>-1.417</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M10</td>
<td>-0.713</td>
<td>-2.261*</td>
<td></td>
<td></td>
</tr>
<tr>
<td>M11</td>
<td>-0.719</td>
<td>-1.788</td>
<td></td>
<td></td>
</tr>
<tr>
<td>PROD_CHANGE_{t-1}</td>
<td></td>
<td>0.328***</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Observations 1,839  1,839
Pseudo R-squared 0.028  0.041
N-Left-censored 243  1,491
N-Clusters 70  70

*** p<0.01, ** p<0.05, * p<0.10. Indicated p-values are one-tailed for coefficients with predicted signs (i.e., ‘(+)) or ‘(-)’ and two-tailed otherwise.
## Appendix: Variable Definitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>POST</strong></td>
<td>1 for the post-introduction period (2008-2010), and 0 for the pre-introduction period (2006-2007)</td>
</tr>
<tr>
<td><strong>FCSTERror</strong></td>
<td>the absolute deviation of the Actual Sales (AS) from the three-month prior Forecasted Sales (FS), i.e., $\text{Error} =</td>
</tr>
<tr>
<td><strong>D_Pos</strong></td>
<td>1 if over forecast (i.e., $\text{FS} &gt; \text{AS}$), and zero otherwise</td>
</tr>
<tr>
<td><strong>D_Neg</strong></td>
<td>1 if under forecast (i.e., $\text{FS} &lt; \text{AS}$), and zero otherwise</td>
</tr>
<tr>
<td><strong>FORWARD</strong></td>
<td>number of months’ sales it takes to sell (based on actual subsequent sales) in inventory at the end of the month prior to the month of production.</td>
</tr>
<tr>
<td><strong>Prod_change</strong></td>
<td>the absolute deviation of logged Actual Production (AP) from logged Planned Production (PP), i.e., $\ln \text{PROD_CHANGE} =</td>
</tr>
<tr>
<td><strong>TREND</strong></td>
<td>product-specific time trend, starting with 1 in the month of product introduction</td>
</tr>
<tr>
<td><strong>EXISTING</strong></td>
<td>1 if the product was an existing product as of the beginning of the sample period, 0 if the product was introduced during the sample period</td>
</tr>
<tr>
<td><strong>PPI</strong></td>
<td>monthly Producer Price Index; measures the average change over time in the selling prices received by domestic producers for their output.</td>
</tr>
<tr>
<td><strong>SALES_VALUE</strong></td>
<td>sales price per unit of measurement (e.g., liters, gallons) multiplied by the pack size (e.g., 100 liters, 2.5 gallons)</td>
</tr>
<tr>
<td><strong>QUANTITY</strong></td>
<td>budgeted sales quantity in physical units</td>
</tr>
<tr>
<td><strong>GMPCT</strong></td>
<td>ratio of gross margin per unit (i.e., sales price minus standard costs) and sales price per unit</td>
</tr>
<tr>
<td><strong>AI_PRODUCTS</strong></td>
<td>captures the number of products that share a certain AI. Higher values indicates greater complexity.</td>
</tr>
<tr>
<td><strong>AI_ALLOCATION</strong></td>
<td>indicates the degree to which the AI is freely available on the market or a scarce resource that needs to be allocated to the products sharing the AI. Higher values indicates greater complexity.</td>
</tr>
<tr>
<td><strong>AI_LIFECYCLE</strong></td>
<td>represents the complexity of the lifecycle management, with new (mature) products being most (least) complex and yielding the highest (lowest) score. Higher values indicates greater complexity.</td>
</tr>
<tr>
<td><strong>AI_FCASTIBILITY</strong></td>
<td>represents the difficulty of forecasting AI demand, with higher values indicating lower complexity. Lower values indicates greater complexity.</td>
</tr>
<tr>
<td><strong>EXPORT</strong></td>
<td>1 if the product is sold outside the United States, and 0 otherwise</td>
</tr>
</tbody>
</table>