

## **Co-opetition and the Firm's Information Environment**

**Brian J. Bushee**

The Wharton School  
University of Pennsylvania  
1300 Steinberg-Dietrich Hall  
Philadelphia, PA 19104-6365  
bushee@wharton.upenn.edu

**Thomas Keusch**

INSEAD  
Boulevard de Constance, 77305  
Fontainebleau, France  
thomas.keusch@insead.edu

**Jessica Kim-Gina**

The Wharton School  
University of Pennsylvania  
1300 Steinberg-Dietrich Hall  
Philadelphia, PA 19104-6365  
jessicak@wharton.upenn.edu

April 2018

*Preliminary and incomplete. Please do not cite.*

The authors are grateful for the funding provided by The Wharton School, INSEAD, the INSEAD-Wharton Alliance, and the Mack Institute for Innovation Management. We thank the Searle Center on Law, Regulation, and Economic Growth at Northwestern University for providing the data on Standard Setting Organizations.

## **Co-opetition and the Firm's Information Environment**

### **Abstract**

Some firms in the technology sector choose to cooperate with competitors (“co-opetition”) in Standards Setting Organizations (SSOs). These SSOs create technology standards that facilitate rapid market penetration of new technologies such as Wi-Fi, Bluetooth, and Blue-Ray. Active participation in the standard setting process requires the exchange of proprietary information with competitors. While the goal of such information sharing is to further a technology or a market, firms potentially receive an unintended benefit from access to competitor and industry information. We examine whether active SSO participation enhances a firm's information set and allows managers to better predict future sales and earnings. Comparing firms that actively contribute information in SSOs with firms that passively participate (i.e., do not share information), we find that SSO-contributing firms are more likely to issue annual sales forecasts after initiating their collaboration. We also find the SSO-contributing firms experience an improvement in the accuracy of their annual sales and earnings forecasts and a reduction in the dispersion of analysts' earnings forecasts. Our findings contribute to the literature by showing that collaborating with competitors in the product market provides an important unintended benefit of improving the manager's information set.

Keywords: Technology, Co-opetition, Information Environment, Management Forecasts  
JEL classification: L14, L15, M41, O32

## 1. Introduction

This paper examines how information sharing among competitors affects a firm's information environment. While extensive prior research focuses on the proprietary costs of disclosure due to product market competition, there is limited research on inter-firm information sharing among competitors. This practice, often referred to as “co-opetition,” involves firms voluntarily collaborating with competitors in a non-collusive, pro-competitive sense.<sup>1</sup> A co-opetitive collaboration often comprises a set of agreements among competitors to make joint efforts on activities such as research and development (R&D), production, marketing, distribution, sales, or purchasing. Sharing of proprietary information is an inevitable and important part of these inter-firm collaborations. While the goal of such information sharing is to promote a technology or a market, firms potentially receive an unintended benefit from access to competitor and industry information, which managers can use to enhance their information set and to better predict future sales and earnings growth. We examine these potential benefits by testing whether the initiation of co-opetitive collaborations is associated with changes in management forecast properties—such as forecast frequency and accuracy—and reductions in analyst forecast dispersion.

We examine technology standard setting organizations (SSOs) as our research setting. SSOs are specialized organizations with open memberships that are comprised of firms, scholars, and engineers who strive to develop technology standards. Standardized technologies allow firms to develop products that work together with their competitors' products (e.g., a Samsung Bluetooth speaker can connect to an Apple iPad). By making their products compatible with competitors'

---

<sup>1</sup> The Federal Trade Commission (FTC) and the U.S. Department of Justice (DOJ) have published the guidelines for collaboration among competitors in order to encourage procompetitive collaborations. They acknowledge that “[c]ompetitive forces are driving firms toward complex collaborations to achieve goals such as expanding into foreign markets, funding expensive innovation efforts, and lowering production and other costs. Such collaborations often are not only benign but procompetitive. Indeed, in the last two decades, the federal antitrust agencies have brought relatively few civil cases against competitor collaborations” (FTC and DOJ, 2000).

products, the firms can take advantage of network effects; i.e., the products' value to the consumer increases with the size of the network of other consumers using the products. Given the increasing importance of technologies and inter-product compatibility, SSOs have become an essential coordination function in technology industries (Farrell and Saloner, 1988; Tushman and Rosenkopf 1992; Garud and Kumaraswamy 1995). SSOs are a powerful setting to study the effects of inter-firm information sharing on the firm's information environment because (1) substantial amounts of proprietary information are exchanged through collaboration at SSOs, (2) the institutional features of SSOs ensure that the information is credible (i.e., firms cannot do "cheap-talk") and (3) participating firms have early access to technical and strategic knowledge that is not readily available to the public.

We obtain a list of 550 firms participating in nine SSOs between 1990 and 2014 from Northwestern's Searle Center on Law, Regulation, and Economic Growth. Each SSO is comprised of a number of working committees that develop standards for certain technology (e.g., the IEEE has an Ethernet Working Group [standard 802.3] and a LAN Working Group [802.11]). Firms can choose how actively they want to participate in the standard setting process. About half of the firms (253) actively contribute to the committees that develop the standards. These "SSO-contributing" firms send their engineers to attend committee meetings and reveal which of the contributing firms' patents are relevant to the standards. The other half (247) are "SSO-passive" firms that never join any committees and only passively participate in the SSO; e.g., by licensing the developed technology. In our research design, we use the SSO-contributing firms as treatment firms, and use their first year of active committee participation as the treatment year. Then, we use propensity score matching to select control firms among the SSO-passive firms. Thus, all of our

sample firms have decided to join SSOs, but differ only in their degree of information sharing with competitors.

We first test whether SSO-contributing firms are more likely to issue management forecasts after initiating active collaboration in their first SSO committee. There are two reasons that active collaboration would increase the likelihood of issuing a forecast. First, prior work finds that firms with high proprietary costs (as proxied by R&D expenditures) are less likely to issue forecasts (Cheng et al. 2005; Wang 2007). Given that SSO-contributing firms are already directly sharing some proprietary information with competitors, they likely face lower incremental proprietary costs in issuing additional public disclosure. Second, prior work finds that earnings predictability is an important factor that drives management forecast issuance (e.g., Waymire 1985; Chen, Matsumoto, and Rajgopal 2011). SSO-contributing firms are able to gather credible information about competitors and markets that complements their firm-specific information set, which should improve the manager's ability to predict sales and earnings. Thus, we predict that the initiation of active committee collaboration will make SSO-contributing firms more likely to issue forecasts.

We test for the effects of SSO information-sharing by examining both sales and earnings forecasts over both annual and quarterly horizons. While each of these forecasts is potentially affected by SSO information transfers, we expect the largest effect to be on sales forecasts and on annual forecasts due to the fact that the standard-setting process most directly affects the sales potential of products over a longer horizon. We find that SSO-contributing firms are significantly more likely to issue sales forecasts after initiating committee collaboration, especially annual forecasts. There is no effect of committee activity on the decision to issue earnings forecasts. Thus, the results support our prediction that inter-firm information sharing increases the likelihood that

managers issue forecasts, but only for annual sales forecasts, suggesting that the competitor information gleaned through SSO collaboration is most useful for resolving uncertainty about product market growth over long horizons.

Next, we predict that SSO-contributing firms will exhibit an improvement in forecast accuracy after initiating active SSO collaboration. Prior work finds that forecast accuracy depends on many factors, such as the firm's complexity; its earnings volatility; the quality of its information system; and the degree to which its earnings are driven by firm-specific factors (versus industry or macroeconomic factors) (see Hirst, Koonce, and Venkataraman 2008 for a review). Prior work also finds that that forecasts by one firm affect the information environment of firms in the same industry (Baginski 1987; Han, Wild, and Ramesh 1989; Pyo and Lustgarten 1990; Kim, Lacina, and Park 2008). In our setting, active SSO participation should allow managers to gather more precise information on industry and macroeconomic effects than could be gleaned from public forecasts of competitors. Thus, we predict that SSO-contributing firms will issue more accurate forecasts (i.e., lower absolute forecast errors) after initiating SSO collaboration.

We find that SSO-contributing firms experience a significant improvement in forecast accuracy for annual sales forecasts in the three years after a firm initiates SSO committee collaboration. We also find significant improvements in accuracy for both annual and quarterly earnings forecasts. Thus, while SSO activity does not alter the cost-benefit trade-off enough to encourage more earnings forecast issuances, it does improve the manager's information set enough to significantly reduce forecast error. These results are consistent with our prediction that actively contributing to SSO committees brings important information benefits to the firm.

Finally, we examine how active SSO participation affects the commonality in the analysts' information sets and, hence, analyst forecast dispersion. Analysts are aware of which firms are

participating in SSOs because they often discuss the firm's SSO activity. Prior work finds that analysts obtain additional information from management forecasts (e.g., Baginski and Hassell, 1990; Jennings, 1987; Williams, 1996). For SSO-contributing firms, analysts will expect their management forecasts to be more accurate and credible due to their access to competitor information. Also, analysts can better forecast industry trends if they know which firms are working together through SSOs. Thus, we predict that SSO-contributing firms have lower analyst forecast dispersion than SSO-passive firms after the initiation of active collaboration. We do not find a significant change in analyst sales forecast dispersion for SSO-contributing firms, indicating that analysts do not appear to consistently incorporate the increased frequency and accuracy of managements' annual sales forecasts into their own sales forecasts. However, consistent with our prediction, we do find that SSO-contributing firms exhibit significant reductions in analyst forecast dispersion for both annual and quarterly earnings forecasts after initiating collaboration.

Our findings contribute to the literature by showing that collaborating with competitors in the product market provides an important unintended benefit of improving the manager's information set and the accuracy of management forecasts. Prior work suggests that proprietary costs can have a significant dampening effect on public disclosures (Verrecchia 1983; Cheng et al. 2005; Wang 2007). Our paper reveals a setting where managers find it advantageous to share some proprietary information with competitors, and in doing so, are able to obtain proprietary competitor information. This private exchange of proprietary information makes it more likely that managers issue forecasts and makes such forecasts more accurate. Prior work also finds evidence of intra-industry information transfers through public disclosure (Baginski 1987; Han, Wild, and Ramesh 1989; Pyo and Lustgarten 1990; Kim, Lacina, and Park 2008). Our findings show that such transfers also happen privately, and are more effective when both parties actively share

information than when they are passive participants in an industry association. Overall, our results suggest that future work should consider the presence of formal structures that facilitate intra-firm information sharing in considering the role of proprietary costs and competitor's disclosures in shaping a firm's information environment.

Section 2 provides institutional background on standard setting organizations. Section 3 reviews prior literature and provides empirical predictions. Section 4 describes the sample and research design. Section 5 presents results and Section 6 concludes.

## **2. Institutional Background**

### *2.1 Co-opetition*

Competitors typically strive for increased market share without participating in collaborative efforts. However, some competitors organize themselves into clusters and collaborate with each other (Bougrain and Haudeville 2002; Ganguli 2007; Levy et al. 2003). This hybrid behavior, which consists of elements of both cooperation and competition, is known as "co-opetition" (Brandenburger and Nalebuff 1995), and has been increasingly popular in technology-related industries that benefit from standardization (Bengtsson and Kock 2000; Chen 2008; Gnyawali et al. 2006).

Prior work finds that co-opetition has both advantages and disadvantages. Through co-opetition, firms can gain beneficial access to additional know-how, skills, and resources (Ma 1999). They can also create a network market where a system of products from different manufacturers inter-operate, resulting in higher consumer utility and greater collective profits for firms. Unlike collusion, co-opetition can be socially desirable as it can practically solve several challenges such as shrinking product life cycles, need for heavy investments in R&D, convergence of multiple technologies, and importance of technological standards (Garud 1994; Gnyawali and

Park 2009; Gomes-Casseres 1994). The main disadvantage of co-opetition is the high risk of opportunism as firms have incentives to defect and to use shared information for their own purposes (Levy et al. 2003; Zerbini and Castaldo 2007).

We examine a potential unintended benefit of co-opetition: an improvement in a firm's information environment. By cooperating with competitors, managers can get additional insights into the performance and investment efforts of their competitors, as well as the industry as a whole. Managers can also learn more quickly about the viability and market potential of new products that are developed within the co-opetitive environment. Finally, managers can control and track the amount of proprietary information they share with competitors in the co-opetitive environment, and thus have a clearer sense of how much, if any, proprietary information would be revealed through public disclosure. Each of these benefits has the potential to affect a manager's voluntary forecasting ability, as well as analysts' use of management forecasts. We study these effects in an important venue for co-opetition: standard setting organizations.

## *2.2 Standard Setting Organizations*

Standard Setting Organizations (SSOs) are voluntary private organizations that aim to create a consensus among technology developers and commercializers as to a set of common standards for the technology.<sup>2</sup> Such a consensus serves as a focal point for industry coordination and leads to a bandwagon process among adopters. Because innovations are typically not promulgated by a single firm, but rather draw together technologies developed in multiple firms, the coordination role played by SSOs has become increasingly critical in the modern economy. Many technology firms invest substantially in these efforts. For example, IBM spent an estimated

---

<sup>2</sup> Historically, governments and regulators have played little role in setting standards. For example, time zones were developed by private railroad companies in the 1800s, and are maintained today by the ISO (International Organization for Standardization), which is an independent, non-governmental organization. This tradition of private standard setting continues today in the tech sector.

\$500 million — roughly 8.5 percent of its R&D budget — on standards development in 2005 alone (Hardy, 2005).

Inter-firm information exchange at SSOs often results in major technological change and growth of the related product markets. Standardization is an important step in a technology life cycle as it facilitates commercialization of the technology. SSOs serve as an open and active forum through which firms exchange information and influence the standard development process. Inter-firm information exchange is the very mechanism through which a technology standard is shaped and accepted. The U.S. Department of Justice allows SSOs to serve as a forum for direct communications among peer firms despite potential collusion concerns because of the societal benefits of the network effects (Garud 1994; Gnyawali and Park 2009; Gomes-Casseres 1994).

Each SSO typically has various technical committees and working groups within the organization (see Appendix A for an example of a SSO and its committees). These committees develop different aspects of a technology standard. Given that the total number of SSO firms is often too large to permit effective discussion, these committees serve to facilitate more effective discussions among participants with similar expertise to contribute. Contributing firms voluntarily choose which committees to join depending on their interests and relevance to each committee. They may contribute to as many committees as they want, or not participate in them at all. In these committees, “firms and other constituencies share technical information, adjudicate technological differences, select standards, and negotiate future developments” (Rosenkopf, Metiu and George 2001). Thus, we expect that firms contributing to committees will have access to much more information about their competitors and about the product market than firms not actively participating in committees. We exploit this differential access to competitive information to test

whether firms that being contributing to committees have improvements in their information environments, relative to a control sample of passive SSO firms that are not participating.

SSO-contributing firms typically have personnel designated to participate in the standard-setting process. Although these representatives have relevant technical knowledge, they are not necessarily engineers who engage in the R&D function at the firms. Nor are they typically the CEO or CFO. If the standard setting process works in isolation from the rest of the firm's information gathering efforts, it would work against us finding an effect of active SSO participation on the firm's information environment. However, we expect that the participating representatives debrief other company personnel after the committee meetings, and that such information is ultimately incorporated by the CFO into sales and earnings forecasts.

### **3. Empirical Predictions**

#### *3.1 Decision to Issue Management Forecasts*

We expect that active SSO participation will be related to a manager's decision to issue forecasts. Prior work finds the managers voluntarily decide to issue forecasts to obtain benefits such as aligning investor expectations; reducing information asymmetry, return volatility, and cost of capital; signaling their ability; and reducing expected litigation costs (e.g., Ajinkya and Gift 1984; Hassell and Jennings 1986; Trueman 1986; King et al. 1990; Skinner 1994; Kasznik and Lev 1995; Coller and Yohn 1997; Billings, Jennings, and Lev 2015). A major deterrent to issuing forecasts is expected proprietary costs (Verrecchia 1983). Consistent with this theory, prior work finds that firms with high R&D expenditures are less likely to issue earnings forecasts and forecast less frequently than low R&D firms (Cheng et al. 2005; Wang 2007).

Another important factor that drives management forecast issuance is predictability. Managers are more likely to issue forecasts when earnings are less volatile and easier to predict

(Waymire 1985; Chen, Matsumoto, and Rajgopal 2011). Prior forecast accuracy affects the credibility of forecasts, suggesting that the decision to forecast is influenced by the firm's prior accuracy (Williams 1996; Hutton and Stocken 2007). Similarly, firms that consistently fall below analyst estimates tend to stop providing forecasts; when they resume, their record of meeting analysts' forecasts improves (Houston et al. 2007). Samuels (2017) finds that firms with improvements in internal information systems due to government contracting increase their forecasting behavior.

Based on this research, there are two reasons to expect that information sharing within SSOs would affect the likelihood of issuing forecasts. First, to the extent that proprietary information is already shared with competitors, firms likely face lower expected proprietary costs in issuing additional public disclosure. Second, the opportunity to gather competitor information should increase the predictability of sales and earnings. Thus, we predict that firms actively contributing to SSO committees will be more likely to issue forecasts after initiating their collaboration, compared to passive SSO firms during the same period (i.e., firms that belong to the SSO, but do not share information in committees).

To provide a comprehensive picture of where SSO information sharing has the biggest impact, we examine forecasts of sales and earnings for both annual and quarterly forecast horizons. We expect a larger effect on annual forecasts because such forecasts are less predictable than quarterly forecasts (Hirst, Koonce, and Venkataraman 2008), and hence there are larger benefits to the additional information gained in SSO activity. We also expect a larger effect for sales forecasts than for earnings forecasts because much of the SSO activity involves commercialization, and hence affects future sales more directly than future earnings.

### *3.2. Management Forecast Accuracy*

We predict that active SSO participation will be related to the accuracy of management forecasts (i.e., the absolute value of the forecast error). Prior work finds that a manager's ability to forecast accurately depends on many factors, including the firm's complexity; the volatility of its earnings; the quality of its accounting and information systems; managerial talent, prior forecasting behavior, and the degree to which its earnings are driven by firm-specific factors (versus industry or macroeconomic factors) (see Hirst, Koonce, and Venkataraman 2008 for a review). Prior work also finds that that forecasts by one firm affect the information environment of firms in the same industry (Baginski 1987; Han, Wild, and Ramesh 1989; Pyo and Lustgarten 1990; Kim, Lacina, and Park 2008). This evidence is consistent with firms in the same industry facing similar economic shocks, production-technology advancements, and government regulations (Schipper 1990). Thus, information about a competitor firm has the potential to greatly improve a manager's information about future industry or macroeconomic effects on sales and earnings.

Active SSO participation allows managers to gather information on industry and macroeconomic effects that are difficult to tease out by only looking at their own firms' information sets. Essentially, active SSO participation should have a similar impact to the information transfer in public forecasts, with the SSO interactions potentially providing information that is more precise because the firm receives finer competitor information than just a forecast. Thus, we predict that firms actively contributing to SSO committees will issue forecasts are more accurate (i.e., lower absolute forecast errors) after initiating their collaboration, compared to passive SSO firms during the same period. Based on similar arguments as above, we expect a larger effect for annual forecasts and for sales forecasts.

### *3.3 Management Forecast Bias and News*

While our primary focus is forecast issuance and accuracy, we also provide descriptive evidence on whether SSO information sharing affects forecast bias and news. Forecast bias is the

unsigned forecast error; i.e., actual results minus management forecast. Prior work finds a pessimistic bias in short-horizon forecasts, as managers attempt to “walk down” analyst forecasts to a beatable level (Chen 2004; Cotter et al. 2006; Bergman and Roychowdhury 2007). In contrast, long-horizon forecasts tend to be optimistically biased (Choi and Ziebart 2004; Rogers and Stocken 2005; Bergman and Roychowdhury 2007). Conditional on this horizon-related bias, managers are more likely to be optimistically biased for strategic reasons like upcoming security offerings, high financial distress, less-competitive industries, lower litigation risk, and high earnings volatility (which masks bias) (see Hirst, Koonce, and Venkataraman 2008 for a review).

Prior work also examines forecast news, which is defined as the management forecast minus the consensus analyst forecast at the time of forecast issuance. Hutton and Stocken (2007) find that bad news forecasts are more common (46% of their sample) than good news (37%) and confirming forecasts (17%). Bad news forecasts are more common for large earnings surprises, for high litigation risk firms, and forecasts near the end of the fiscal period (Kasznik and Lev 1995; Anilowski, Feng, and Skinner 2007).

We do not make directional predictions for how inter-firm information transfers would affect forecast bias and news because the association is unclear *ex ante*. To the extent that managers use bias and news strategically, better information through SSO activity could allow them to more precisely bias their forecasts. For example, a manager wishing to issue a pessimistically biased forecast to walk down expectations would be able to do so more precisely with a richer information set. In contrast, if a certain bias or news in forecasts prior to SSO participation reflects a rational response to a certain information deficiency (e.g., avoid good news forecasts because they are less certain without information on competitors), then the improved information from SSO participation could lead to more unbiased and confirming forecasts. Thus, we do not make

predictions for these results, but rather provide them as descriptive evidence on how SSO information sharing affects other forecast properties.

### *3.4 Analyst Forecast Dispersion*

Finally, we examine how SSO participation affects analyst forecasts. Prior work finds that analysts revise their forecasts after management forecasts, generally in the same direction as the management forecast news (Jennings, 1987; Hassell et al., 1988; Baginski and Hassell 1990; Williams, 1996; Hansen and Noe 1999). Such analyst forecast revisions are greater when the forecasting manager has higher high prior forecast accuracy (Williams 1996). In addition to using management forecasts to improve their forecasts, prior work finds that analysts glean useful information from managers through additional disclosures such as conference calls and conference presentations (Mayew, Sharp, and Venkatachalam 2013; Green, Jame, Markov, and Subasi 2014).

Analysts are aware of which firms are participating in SSOs because their questions during conference presentations and their narratives in analyst reports often discuss the firm's SSO activity (see Appendix B for examples). There are three potential mechanisms for a firm's active SSO participation to affect analyst forecasts; specifically, reduce forecast dispersion by creating more commonality in the analysts' information sets. First, analysts will expect management forecasts to become more accurate once firms have access to competitor information through SSO information sharing. Second, managers can provide analysts better supplemental information through conference presentations and conference calls when they are active in the SSO. Third, analysts can better forecast industry trends if they know which firms are working together through SSOs. Thus, we predict that firms actively contributing to SSO committees will have lower analyst forecast dispersion after initiating their collaboration, compared to passive SSO firms during the same period.

## **4. Data, Sample Construction, and Empirical Design**

### *4.1 Data*

We collect data on accounting and stock market information from the intersection between CRSP and Compustat, management forecast and analyst forecast information from IBES, and data on firms' past patent output from Noah Stoffman's website (Kogen et al., 2017).

We obtain the list of SSO participants and committee contributors for nine SSOs between 1996 and 2014 from Northwestern's Searle Center on Law, Regulation, and Economic Growth. Panel A of Table 1 lists the nine SSOs, together with examples of their standards and the number of participating firms. The total number of participants in the nine SSOs is 847. Some firms participate in multiple SSOs; the number of unique firms in the data is 550. The largest SSOs in the sample are those that issue standards for computing networks (20.5% of the sample), telecom (19.6%), and wireless networks (14.5% and 8.6% in two SSOs).

Using this data, we can identify whether a given firm participates passively in the SSO (e.g., by licensing the developed technology) or contributes actively to the committee meetings during which the standards are actually developed. There are 1,679 committees in our data, with a mean of 2.87 sample firms per committee and the number ranging from 1 to 71 (note, these numbers only include committee members that are covered by CRSP-Compustat).

### *4.2 Sample Construction*

Our treatment sample includes firms that actively contribute to an SSO committee. We identify the treatment year as the first time a treatment firm makes a contribution to any SSO committee. Panel A of Table 2 shows that, among the 550 unique firms in the SSO dataset, 253 are first-time participants in a committee (i.e., treatment firms) and 247 are only passive participants that never contribute to a committee. After removing 108 treatment firms that are not in the CRSP-Compustat universe and an additional 26 firms that are missing values of variables

for the propensity score matching (PSM) model (see below), we have 119 treatment firms in the PSM model.

Panel B of Table 2 shows the number of first-time contributors by year during our sample period. We observe the largest number of first-time contributions in 1997, which is when a number of SSO committees were formed; e.g., DVD standards and ETSI Wireless Network standards. Panel C documents the sample composition of first-time contributors in terms of two-digit SIC industry membership. The most frequent industries are Electronic and Other Electrical Equipment and Components, Except Computer (SIC code 36; 34.5% of the sample), Industrial and Commercial Machinery and Computer Equipment (SIC code 35; 15.1%), Business Services (SIC code 73; 14.3%), and Communications (SIC code 48, 9.2%). We will include year and industry fixed-effects in the analyses to account for any effects of clustering of observations.

We construct a pool of candidate firm-years from which we ultimately select the control firm-years as follows. First, for treatment firms, we include all years that satisfy two criteria: (1) the firm is passively participating in an SSO in that year and (2) the year is earlier than the first-time contribution year. Thus, a firm is dropped from the pool of candidates in the year that it makes its first contribution to a committee. Second, for firms that never actively contribute to a SSO committee, we include all years during which the firm is a passive member of the SSO.

We estimate the PSM logit model on this sample of treatment and candidate firms. We include a number of variables that potentially explain incentives to participate in an SSO committee for the first time. SSO committee contribution is costly because contributors have to send engineers to committee meetings, to identify internally which of their patents a new technology might infringe on, and to disclose those patents to other contributors. Larger and more profitable firms have more resources available to make costly contributions to SSO committees.

R&D-intensive firms are more likely involved in the actual development of new technologies than firms that do not engage in R&D, who are likely to license the technologies from contributors once development is completed. Finally, firms with more growth options likely have a prospector strategy and strive to pioneer the commercialization of new technologies rather than be a second-mover by licensing new technologies from others. Thus, the variables that we include in the logit model include firm size ( $\ln(Assets)$ ), R&D intensity ( $R\&D / Assets$ ), profitability ( $ROA$ ), and growth opportunities as measured by the book-to-market ratio ( $Book / Market$ ) and by sales growth ( $Sales Growth$ ). All of these variables are lagged by one year.

Panel A of Table 3 shows the results of the logit model. The number of observations is 1,191, which includes the treatment firm-years and candidate firm-years using the algorithm described above. We find that firm size, R&D intensity, and sales growth are positively and significantly associated with the probability of a first-time committee contribution.

We use the propensity scores from this model to choose control firms from the pool of candidate firm-years. We select a maximum of three control firm-years per treated firm-year using nearest-neighbor matching without replacement. We select three control firm-years in order to increase the power of our tests. For every match, we impose the constraint that the control observation must come from the same fiscal year as the treated observation to mitigate the influence of potentially unobservable differences between treated and control observations that are related to the time period. The fact that all treatment observations and all control observations are participants in SSOs further increases the similarity between treatment and control observations.<sup>3</sup>

---

<sup>3</sup> Since we measure treatment at the firm-year level rather than the firm-year-SSO level, and since several firms participate in many SSO and contribute to several committees at the same time, we cannot match treatment firms to control firms strictly within the same SSO.

We are unable to find close matches for 31 treatment firms, bringing our final sample of treatment firms down to 88 firm-years. We are able to find 227 control firm-years for our matched sample.

In Panel B of Table 3, we examine whether the PSM approach achieves covariate balance on the variables used in the logit regression, as well as on other firm characteristics. We find no significant differences for total assets, R&D, profitability, book-to-market, and sales growth, with the lowest two-tailed p-value being 0.2 ( $\text{Ln}(\text{Assets})$ ). In addition, we find that the means of treatment and control observations are indistinguishable from each other for stock return volatility (*Return Volatility*), whether or not a firm issues sales or EPS guidance (*Sales Guidance*, *EPS Guidance*), cash holdings (*Cash / Assets*), leverage (*Debt / Assets*), investments in fixed assets (*Capex / Assets*), the number of years since the firm first appeared on CRSP (*Firm Age*), and stock market capitalization ( $\text{Ln}(\text{Market Cap})$ ).

The only characteristic that differs significantly between treatment and control observations is the number of patents a firm was granted over the past five years ( $\text{Ln}(\# \text{ Patents})$ ), which is significantly greater for treatment firms. This variable is only available until the year 2011. Hence, we do not match on this variable to avoid losing additional observations, but we run all our subsequent analyses with and without controlling for this variable.

#### 4.3 Research Design

To examine whether management and analyst forecast properties change for SSO-contributing firms around the time of their initial contribution, we estimate difference-in-differences analyses. For each treatment firm and control firm, we keep any of the three years before and after the treatment or placebo year if we have data on the firm's SSO, the dependent variable, and control variables for that year. The empirical specification that we use throughout our analyses is as follows

$$DV = \alpha_t + \alpha_{SIC2} + \beta * \text{Treatment} + \gamma * \text{Post} + \lambda * \text{Treatment} * \text{Post} + v * \text{Controls} + \varepsilon \quad (1)$$

where  $\alpha_t$  and  $\alpha_{SIC2}$  are year fixed effects and two-digit SIC industry fixed effects, respectively, and standard errors are clustered by firm. *Treatment\*Post* is the difference-in-differences estimator.

We examine a number of dependent variables (DV), and the unit of analysis differs depending on the DV. When the DV is an indicator for management earnings or sales forecasts in a given year (*EPS Forecaster* or *Sales Forecaster*) or the frequency of management earnings or sales forecasts per year (*EPS Forecast Freq* or *Sales Forecast Freq*), the unit of analysis is at the firm-year level. When the DV is management forecast accuracy, bias, or news, the unit of analysis is at the forecast level. We define management forecast accuracy (*Abs(Error)*) as the unsigned difference between actual EPS (or sales) and the management forecast of EPS (or sales), scaled by share price (or actual sales). Similarly, we define management forecast bias (*Bias*) as the signed difference between actual EPS (or sales) and the management forecast of EPS (or sales), scaled by share price (or actual sales). We define management forecast news (*News*) as the signed difference between the management forecast of EPS (or sales) and the analyst consensus forecast of EPS (or sales) at the time of the forecast, scaled by share price (or actual sales). Finally, when the dependent variable is analyst forecast dispersion (*Dispersion*), the unit of analysis is at the firm-month level. We calculate *Dispersion* as either the standard deviation of all EPS forecasts provided by unique analysts in a given firm-month, scaled by share price, or the standard deviation of all sales forecasts, scaled by actual sales. We require at least two forecasts to compute the dispersion measures.

Table 4 presents descriptive statistics on the DVs. Panel A reports firm-year level management forecast issuance variables. Almost half of the sample issues sales (45.8%) and earnings (47.2%) forecasts in a given year, with quarterly forecasts more commonly issued than annual forecasts (~38% vs. ~23%). The mean number of forecasts is around 2.3 per year.

Panel B reports the management forecast properties variables, which are measured at the forecast level. As expected, quarterly EPS forecasts (mean  $Abs(Error) = 0.005$ ) are more accurate than annual EPS forecasts (mean  $Abs(Error) = 0.011$ ). However, sales forecasts exhibit almost the same accuracy between annual and quarterly forecasts (mean  $Abs(Error) = 0.058$  and  $0.060$ , respectively). Consistent with prior work, the mean  $Bias$  for both sales and EPS forecasts is positive, which reflects a pessimistic bias in the forecast (i.e., actual EPS is greater than the forecast). Also consistent with prior work, the mean  $News$  for both types of forecasts is negative, which reflects a greater incidence of bad news forecasts (vis-à-vis the consensus analyst forecast at the time).

Panel C reports the analyst forecast dispersion variables, which are measured at the firm-month level. As expected, analyst forecast dispersion is larger for annual forecasts than for quarterly forecasts.

## **5. Empirical Results**

### *5.1 Decision to Issue Management Forecasts*

We first test whether inter-firm information sharing through SSO committee participation is associated with a greater likelihood of issuing a management forecast. We estimate equation (1) with the DV as an indicator for sales or earnings forecast issuances during a firm-year (*Sales Forecaster* or *EPS Forecaster*). We estimate models that use all forecast horizons, annual forecasts only, and quarterly forecasts only. We also estimate a model on the full sample and on a restricted sample that includes a control for patent data (which is only available until 2011).

Table 5, Panel A presents results for sales forecast issuances. For all forecast horizons (columns (1) and (2)), the coefficient on  $Treatment * Post$  is positive and significant, indicating that firms are more likely to issue sales forecasts after they initiate active contributions to an SSO committee for the first time. This result is largely driven by the issuance of annual sales forecasts,

as *Treatment \* Post* is positive and significant in the annual forecast regression (columns (3) and (4)), but positive and insignificant in the quarterly forecast regression. These results hold regardless of whether we include a control for patent activity. Interestingly, the coefficient on *Treatment* is negative and significant in the annual forecast regression. Thus, SSO-contributing firms were less likely to issue annual sales forecasts than control firms prior to initiating cooperation, and become more likely afterwards, indicating that the forecasting benefits of information sharing are large for such firms.

Panel B presents results for EPS forecasts. The coefficient on *Treatment \* Post* is not significantly different from zero in any of the models. Thus, information sharing in SSO committees provides benefits for forecasting annual sales, but has seemingly little impact on encouraging earnings forecasts.

We also estimate the models with the DV as the number of sales or earnings forecasts issued during the firm-year (*Sales Forecast Freq* or *EPS Forecast Freq*). The results are identical to the indicator variable specification; the coefficients on *Treatment \* Post* are positive and significant for all and annual sales forecasts, and insignificant for quarterly sales and all EPS forecasts (untabed). Overall, the results support our prediction that SSO information sharing increases the likelihood that managers issue forecasts, but only for annual sales forecasts, suggesting that the industry and competitor information gleaned through SSO collaboration is most useful for resolving uncertainty about product market growth over long horizons.

## 5.2. Management Forecast Accuracy

One drawback to the forecast issuance results is that managers are trading off other benefits and costs of issuing forecasts. It is possible that the benefits from the SSO collaboration are not be large enough to overcome these other factors in the decision. Thus, we next look only at firms that have decided to issue forecasts to test whether the information gained through SSO activities has

a significant effect on forecast accuracy. The DV in these regressions is the unsigned difference between the actual sales or earnings and the management forecast of sales or earnings (*Sales Abs(Error)* or *EPS Abs(Error)*). We again estimate models separately for annual and quarterly forecasts and for the full sample and patent-data sample.<sup>4</sup> We also include an indicator variable that is equal to one for management forecasts that are a revision of a prior forecast and equal to zero for initial forecasts (*Forecast Revision*).

Panel A of Table 6 presents results for sales forecasts. The coefficients on *Treatment \* Post* are negative and significant for the annual sales forecast models, indicating that annual sales forecast accuracy improves in the three years after a firm initiates SSO committee collaboration. The benefits of collaboration again seem to be smaller for quarterly sales forecasts, as the coefficients on *Treatment \* Post* are insignificant in the quarterly forecast model.

Panel B presents results for earnings forecasts. For both annual and quarterly forecasts, the coefficients on *Treatment \* Post* are negative and significant, consistent with inter-firm information transfer in SSOs improving the accuracy of EPS forecasts. Thus, while SSO activity does not alter the cost-benefit trade-off enough to encourage more earnings forecast issuances, it does improve the company's information set enough to significantly reduce forecast error. These results are consistent with our prediction that actively contributing to SSO committees brings information benefits to the firm, leading to more accurate forecasts.

Notably, Table 6 shows that, for both sales and earnings forecasts, the coefficients on *Treatment* are positive and significant. This result indicates that, prior to their first-time contributions, SSO-contributing firms have less accurate forecasts than control firms, which is consistent with such SSO-contributing firms having more uncertainty about how competitors'

---

<sup>4</sup> We do not combine annual and quarterly forecasts together in this analysis because the magnitudes and standard deviations of the forecast errors are very different between annual and quarterly forecasts.

actions will affect their long-horizon earnings and sales forecasts. Through active collaboration with competitors, these treatment firms are then able to close the information gap and issue significantly more accurate forecasts.

### 5.3. Management Forecast Bias and News

Although it is *ex ante* unclear how inter-firm information sharing in SSOs would affect forecast bias and news, we provide descriptive evidence on whether better competitor information is associated with changes in bias and news of management forecasts.

Table 7 presents the results of estimating equation (1) with a DV of forecast bias, defined as the signed difference between the actual amount and the management forecast. Panel A shows results for sales forecasts. The coefficients on *Treatment* are negative and significant for both annual and quarterly forecasts, indicating a more optimistic bias for treatment firms prior to initiating SSO committee activity. After the first-time contribution to an SSO, the optimistic bias is mitigated, as evidenced by the positive and significant coefficient on *Treatment \* Post* in all specifications.<sup>5</sup> Thus, it appears that SSO-contribution firms have an optimistic view of their product's sales potential before actively engaging in the SSO; once they have access to their competitor's information, their forecasts exhibit the same level of pessimistic bias as the control firms (as evidence by the insignificant *p*-value in the last row for the test: *Treatment + Treatment \* Post = 0*).

Panel B of Table 7 shows that the coefficients on *Treatment \* Post* are insignificant in all specifications. Thus, inter-firm information sharing does not affect bias in earnings forecasts.

---

<sup>5</sup> Because the specifications include industry-year fixed effects, which would represent the bias for control firms prior to their pseudo-event date, it is difficult to see whether the coefficients represent an absolute optimistic or pessimistic bias. The mean bias in annual sales forecasts for control firms in the pre period is 0.023. Using the coefficients in column (2) for annual sales, this means that treatment firms had a mean optimistic bias of -0.073 in the pre period ( $0.023 - 0.096$ ), which flips to a mean pessimistic bias of 0.024 in the post period ( $0.023 - 0.096 - 0.009 + 0.106$ ).

Table 8 presents the results of estimating equation (1) with a DV of forecast news, defined as the signed difference between the management forecast and the consensus analyst forecast at the time of management forecast issuance. Panel A shows results for sales forecasts. Again, the coefficients on *Treatment* are negative and significant for both annual and quarterly forecasts, indicating a tendency to provide more bad news forecasts prior to commencing SSO committee activity. In the case of annual forecasts, the coefficients on *Treatment \* Post* are positive and significant, which mitigates the greater bad news bias of treatment firms.<sup>6</sup> This finding is only seen for annual sales forecasts, as the coefficients on *Treatment \* Post* are insignificant for quarterly sales forecasts and, in Panel B, for annual and quarterly earnings forecasts (with the exception of one marginally significant coefficient for quarterly earnings in the full sample).

Putting these findings together, the evidence suggests that, prior to the treatment year, SSO-contributing firms issue more pessimistic forecasts (compared to analyst consensus) than control firms. In addition, prior to the treatment year, SSO-contributing firms issue more positively biased forecasts (compared to realizations) than control firms. However, in the post treatment period, all significant differences in forecast news and bias between treated and control firms disappear.

#### 5.4. Analyst Forecast Dispersion

Our final analysis examines whether active SSO participation has a spill-over effect on analysts' information sets, leading to less dispersion in their forecasts. We estimate firm-month specifications of equation (1) using a DV of analyst dispersion, which is either the standard

---

<sup>6</sup> The mean news of annual sales forecasts for control firms in the pre period is -0.014. Using the coefficients in column (2), this means that treatment firms had a mean news of -0.057 in the pre period ( $-0.014 - 0.043$ ) and -0.019 in the post period ( $-0.014 - 0.043 - 0.004 + 0.042$ ). Thus, treatment firms still exhibit a bad news bias, but it is much closer to zero.

deviation in analyst EPS forecasts, scaled by price, or the standard deviation of analyst sales forecasts, scaled by actual sales.

Panel A of Table 9 presents results for sales forecasts. Across all specifications, for both quarterly and annual analyst sales forecasts, we find no significant differences in forecast dispersion between SSO-contributors and control firms. Thus, while SSO-contributing firms are more likely to issue annual sales forecasts after initiating collaboration, and while such forecasts are more accurate, analysts do not appear to consistently incorporate this information into their sales forecasts.

Panel B shows the results for earnings forecasts. Consistent with our prediction, the coefficients on *Treatment \* Post* are negative and significant for three of the four specifications (with the  $p$ -value = 0.105 in the fourth), providing evidence of a reduction in dispersion for forecasts of SSO-contributing firms after their first committee collaboration. This finding suggests that, in the case of earnings forecasts, the increased credibility of the more accurate management forecasts and the analysts' ability to observe which firms are active collaborating combine to increase the commonality among analysts' information sets, and hence reduce earnings forecast dispersion for treatment firms.

## **6. Conclusion**

This paper shows that actively collaborating with competitors (“co-opetition”) creates unintended benefits for a firm’s information environment. Firms that actively share proprietary information with competitors in Standard Setting Organizations (SSO) are more likely to issue annual sales forecasts after initiating collaboration, relative to a matched sample of control firms that passively belong to the SSO. SSO-contributing firms also experience an improvement in the accuracy of annual sales and earnings forecasts, as well as a reduction in the dispersion of analysts’

earnings forecasts. Thus, through active collaboration with competitors, SSO-contributing firms are able to access competitor and industry information, which increases the likelihood that managers issue forecasts and allows managers to issue more accurate forecasts.

Our findings are subject to a number of caveats. First, the information benefits of co-opetition are not widespread and are concentrated in longer-horizon product market information. Thus, while we find consistent evidence that initiating active SSO contributions affects annual sales forecasts, the results are less consistent (or insignificant) for earnings forecasts and for quarterly forecasts. Second, prior to initiating SSO information sharing, SSO-contributing firms exhibit different levels of forecast accuracy, as well as forecast bias and news, than SSO-passive firms. While we use propensity score matching to find control firms that would have similar incentives to contribute to an SSO based on size, growth, and R&D activity, there are still differences in terms of prior management forecast properties. Thus, we must be cautious about attributing causality to initiating active contributions to an SSO. However, it is unlikely the treatment firms decided to actively contribute to the SSO for forecasting benefits, which are almost certainly a second-order concern relative to the product market incentives for SSO participation. Our results are consistent with unintended information benefits to SSO participation, but we acknowledge the possibility exists that such benefits may have been a first-order determinant of active SSO participation.

In any case, our results suggest that future work should consider the presence of formal co-opetitive structures that facilitate inter-firm information sharing when examining the role of proprietary costs and competitor's disclosures in shaping a firm's information environment.

## REFERENCES

- Ajinkya, B. B., and Gift, M. J. (1984). Corporate Managers' Earnings Forecasts and Symmetrical Adjustments of Market Expectations. *Journal of Accounting Research*, 22(2), 425.
- Anilowski, C., M. Feng, and D. J. Skinner. (2007). Does earnings guidance affect market returns? The nature and information content of aggregate earnings guidance. *Journal of Accounting and Economics* 44 (1-2): 36-63.
- Baginski, S. P. (1987). Intraindustry Information Transfers Associated with Management Forecasts of Earnings. *Journal of Accounting Research*, 25(2), 196.
- Baginski, S., and Hassell, J. (1990). The market interpretation of management earnings forecasts as a predictor of subsequent financial analyst forecast revision. *The Accounting Review*, 65(1), 175–190.
- Baron, J., & Spulber, D. F. (2017). Technology Standards and Standard Setting Organizations: Introduction to the Searle Center Database. *SSRN Electronic Journal*.
- Baron, J., & Pohlmann, T. C. (2018, January 31). Mapping Standards to Patents Using Declarations of Standard-Essential Patents. *SSRN Electronic Journal*.
- Bengtsson, M., and Kock, S. (2000). "Coopetition" in Business Networks—to Cooperate and Compete Simultaneously. *Industrial Marketing Management*, 29(5), 411–426.
- Bergman, N., and S. Roychowdhury. (2007). Investor sentiment, expectations, and corporate disclosure. Working paper, MIT Sloan School of Management.
- Billings, M., R. Jennings, and B. Lev (2015). On guidance and volatility. *Journal of Accounting and Economics*, 60(2–3), 161-180.
- Bougrain, F., and Haudeville, B. (2002). Innovation, collaboration and SMEs internal research capacities. *Research Policy*, 31(5), 735–747.
- Brandenburger, Adam M., and Barry J. Nalebuff. The right game: Use game theory to shape strategy. *Harvard Business Review*, 1995.
- Chen, M.-J. (2008). Reconceptualizing the Competition— Cooperation Relationship. *Journal of Management Inquiry*, 17(4), 288–304.
- Chen, S. (2004). Why do managers fail to meet their own forecasts? Working paper, University of Washington.
- Chen, S., Matsumoto, D., and Rajgopal, S. (2011). Is silence golden? An empirical analysis of firms that stop giving quarterly earnings guidance. *Journal of Accounting and Economics*, 51(1–2), 134–150.

- Cheng, M., K. R. Subramanyam, and Y. Zhang. (2005). Earnings guidance and managerial myopia. Working paper, University of Southern California.
- Chiao, B., J. Lerner, J. Tirole. (2007). The rules of standard setting organizations: An empirical analysis. *RAND J. Econom.* 38(4) 905-930.
- Choi, J. H., and D. A. Ziebart. (2004). Management earnings forecasts and the market's reaction to predicted bias in the forecast. *Asia-Pacific Journal of Accounting and Economics* 11 (2): 167-192.
- Coller, M., and Yohn, T. L. (1997). Management forecasts and information asymmetry: An examination of bid-ask spreads. *Journal of Accounting Research*, 35(2), 181–191.
- Cotter, J., I. Tuna, and P. Wysocki. (2006). Expectations management and beatable targets: How do analysts react to public earnings guidance? *Contemporary Accounting Research* 23 (3): 593-624.
- Farrell, J., and Saloner, G. (1988). Coordination Through Committees and Markets. *The RAND Journal of Economics*, 19(2), 235.
- Ganguli, S. (2007). Coopetition Models in the Context of Modern Business. *ICFAI Journal of Marketing Management*, 6(4), 6–16.
- Garud, R. (1994). Cooperative and competitive behaviors during the process of creative destruction. *Research Policy*, 23(4), 385–394.
- Garud, R., and Kumaraswamy, A. (1995). Technological and organizational designs for realizing economies of substitution. *Strategic Management Journal*, 16(1 S), 93–109.
- Gnyawali, D. R., and Park, B.-J. J. (2009). Co-opetition and technological innovation in small and medium-sized enterprises: A multilevel conceptual model. *Journal of Small Business Management*, 47(3), 308–330.
- Gnyawali, D. R., He, J., and Madhavan, R. (“Ravi”). (2006). Impact of Co-Opetition on Firm Competitive Behavior: An Empirical Examination. *Journal of Management*, 32(4), 507–530.
- Green, T. C., Jame, R., Markov, S., and Subasi, M. (2014). Access to management and the informativeness of analyst research. *Journal of Financial Economics*, 114(2), 239–255.
- Han, J. C. Y., Wild, J. J., and Ramesh, K. (1989). Managers’ earnings forecasts and intra-industry information transfers. *Journal of Accounting and Economics*, 11(1), 3–33.
- Hansen, Glen A., and Christopher F. Noe. When is Managers' Earnings Guidance Most Influential?. Division of Research, Harvard Business School, (1999).

- Hardy, Quentin. "IBM's Software Gambit." *Forbes*, 26 Sept. (2005).
- Hassell, J. M., and Jennings, R. H. (n.d.). Relative Forecast Accuracy and the Timing of Earnings Forecast Announcements. *The Accounting Review*. American Accounting Association.
- Hassell, J. M., and R. Jennings. ((1986)). Relative forecast accuracy and the timing of earnings forecast announcements. *The Accounting Review* 61 (1): 58-75.
- Hirst, D. E., Koonce, L., and Venkataraman, S. (2008). Management earnings forecasts: A review and framework. *Accounting Horizons*, 22(3), 315–338.
- Houston, J., B. Lev, and J. W. Tucker. (2007). To guide or not to guide? Causes and consequences of stopping and subsequently resuming earnings guidance. Working paper, University of Florida.
- Hutton, A. P., G. S. Miller, and D. J. Skinner. (2003). The role of supplementary statements with management earnings forecasts. *Journal of Accounting Research* 41 (5): 867-890.
- Jennings, R. (1987). Unsystematic security price movements, management earnings forecasts, and revisions in consensus analyst earnings forecasts. *Journal of Accounting Research* 25 (1): 90-110.
- Jennings, R. (1987). Unsystematic Security Price Movements, Management Earnings Forecasts, and Revisions in Consensus Analyst Earnings Forecasts. *Journal of Accounting Research*, 25(1), 90.
- Kaszniak, R., and Lev, B. (1995). To warn or not to warn: Management disclosures in the face of an earnings surprise." *Accounting review*: 113-134.
- Kim, Y., Lacina, M., and Park, M. S. (2008). Positive and negative information transfers from management forecasts. *Journal of Accounting Research*, 46(4), 885–908.
- King, R., G. Pownall, and G. Waymire. (1990). Expectations adjustment via timely earnings forecast disclosure: Review, synthesis, and suggestions for future research. *Journal of Accounting Literature* 9: 113-44.
- Kogan, L., Papanikolaou, D., Seru, A., and Stoffman, N. (2017). Technological innovation, resource allocation, and growth. *The Quarterly Journal of Economics*, 132(2), 665-712.
- Levy, M., Loebbecke, C., and Powell, P. (2003). SMEs, co-opetition and knowledge sharing: the role of information systems. *European Journal of Information Systems*, 12(1), 3–17.
- Ma, H. (1999). Anatomy of competitive advantage: a SELECT framework. *Management Decision*, 37(9), 709–718.

- Mayew, W. J., Sharp, N. Y., and Venkatachalam, M. (2013). Using earnings conference calls to identify analysts with superior private information. *Review of Accounting Studies*, 18(2), 386–413.
- Pyo, Y., and Lustgarten, S. (1990). Differential intra-industry information transfer associated with management earnings forecasts. *Journal of Accounting and Economics*, 13(4), 365–379.
- Rogers, J. L., and P. C. Stocken. (2005). Credibility of management forecasts. *The Accounting Review* 80 (4): 1233-1260.
- Rosenkopf, L., Metiu, A., and George, V. P. (2001). From the Bottom Up? Technical Committee Activity and Alliance Formation. *Administrative Science Quarterly*, 46(4), 748.
- Schipper, K. (1990). Information Transfers. *Accounting Horizons*, 4(4), 97.
- Skinner, D. J. (1994). Why Firms Voluntarily Disclose Bad News. *Journal of Accounting Research*, 32(1), 38.
- The Federal Trade Commission and the U.S. Department of Justice. 2000. Antitrust Guidelines for Collaborations Among Competitors.
- Trueman, B. (1986). Why do managers voluntarily release earnings forecasts? *Journal of Accounting and Economics*, 8(1), 53–71.
- Tushman, M. L., and Rosenkopf, L. (1992). Organizational Determinants of technological change: Toward a Sociology of Technological Evolution. *Research in Organizational Behavior*.
- Verrecchia, R. E. (1990). Information quality and discretionary disclosure. *Journal of Accounting and Economics*, 12(4), 365–380.
- Wang, I. (2007). Private earnings guidance and its implications for disclosure regulation. *The Accounting Review* 82: 1299-1332.
- Waymire, G. (1984). Additional evidence on the information content of management earnings forecasts. *Journal of Accounting Research* 22 (2): 703-718.
- Williams, P. A. 1996. The relation between a prior earnings forecast by management and analyst response to a current management forecast. *The Accounting Review* 71 (1): 103-115.
- Zerbini, F., and Castaldo, S. (2007). Stay in or get out the Janus? The maintenance of multiplex relationships between buyers and sellers. *Industrial Marketing Management*, 36(7 SPEC. ISS.), 941–954.

## **Appendix A**

### **Examples of Standard Setting Process and Working Committees**

*What are standards?*

“Standards are published documents that establish specifications and procedures designed to maximize the reliability of the materials, products, methods, and/or services people use every day. Standards address a range of issues, including but not limited to various protocols to help maximize product functionality and compatibility, facilitate interoperability and support consumer safety and public health” (Source: Institute of Electrical and Electronics Engineers Standards Association [IEEE-SA] website).

*How are standards made?*

1. Initiating the Project
  - The development of a new standard is triggered by a formal request, submitted to an SSO by a Sponsoring Body (individual or entity) for review and evaluation.
2. Mobilizing the Working Group
  - Once the SSO approves the request, the sponsor follows the SSO rules to assemble a collaborative team or "Working Group" to engage in active standards development. Working Groups are comprised of individuals and/or entities (e.g., people, companies, organizations, non-profits, government agencies) who volunteer to support the development of the standard.
3. Drafting the Standard
  - Participants may contribute at varying levels to the standards development process, based on the rules and criteria established by the SSO. SSOs often have detailed rules to ensure that highly dedicated individuals lead participation and no one interest dominates the standards development process.
  - These activities fuel the gradual definition of each standard, which is compiled into a draft standard that may undergo multiple revisions.
4. Balloting the Standard
  - Once a draft standard has been finalized, reviewed, and approved by the Working Group, it is submitted to the Sponsor for Sponsor balloting. Upon successful completion of the Sponsor ballot, the draft is submitted to the Review Committee. The balloted draft is reviewed by Review Committee and then submitted to the Standards Board for approval.
5. Gaining Final Approval
  - After submission, review, and acceptance, the approved standard is published and made available for distribution and purchasing within in a number of outlets, including through the SSO itself.
6. Maintaining the Standard
  - It is important to remember that standards are “living documents”. Standards may initially be published and iteratively modified, corrected, adjusted and/or updated based on market conditions and other factors. (Source: IEEE-SA website).

**Appendix A (continued)**  
**Examples of Standard Setting Process and Working Committees**

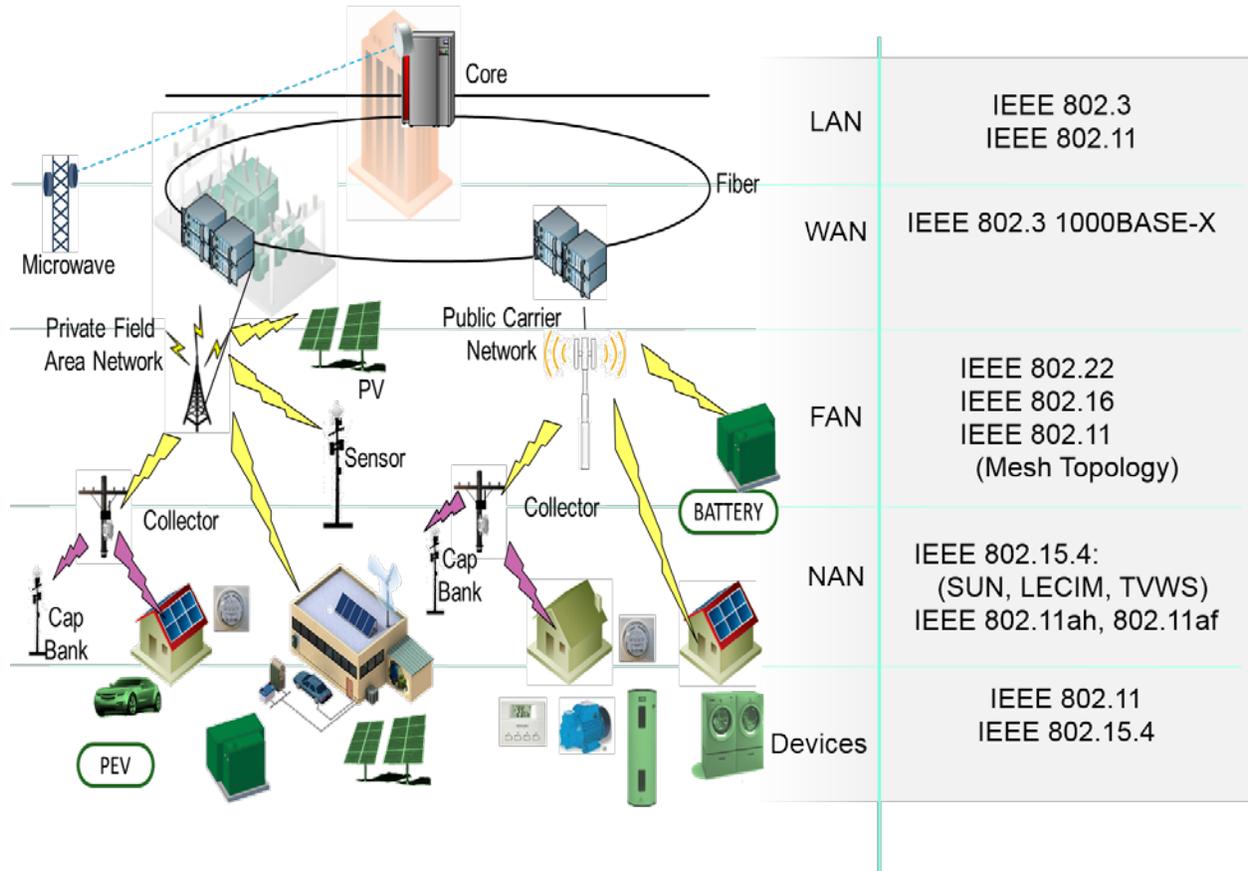
*Example of Working Groups in an SSO*

SSO: IEEE-SA (Institute of Electrical and Electronics Engineers Standards Association)

Standard: IEEE 802 LAN/MAN Standards (source: <http://www.ieee802.org/>)

- The IEEE 802 LAN/MAN Standards Committee develops and maintains networking standards and recommended practices for local, metropolitan, and other area networks, using an open and accredited process, and advocates them on a global basis. An individual Working Group provides the focus for each area.

**Key Standards for Integrated Grid Communications Networks**



**Appendix A (continued)**  
**Examples of Standard Setting Process and Working Committees**

IEEE 802 Working Groups:

- 802.3 Ethernet Working Group develops standards for Ethernet networks.
- 802.11 Wireless LAN Working Group develops standards on wireless local area networks (LAN).
- 802.15 Wireless Personal Area Network (WPAN) Working Group develops Personal Area Network standards for short distance wireless networks.
- 802.16 Broadband Wireless Access Working Group develops standards and recommended practices to support the development and deployment of broadband Wireless Metropolitan Area Networks.
- 802.21 Media Independent Handover Services Working Group is developing an extensible Media access Independent Services (MIS) framework (i.e., function and protocol) that enables the optimization of services including handover service when performed between heterogeneous IEEE 802 networks.
- 802.22 Wireless Regional Area Networks develops a wide variety of standards to enable spectrum sharing.

List of companies in Working Groups<sup>7</sup>

IEEE 802.11 (LAN & Devices)	IEEE 802.3 (Ethernet)	IEEE 802.11.22 (FAN)
AIRONET WIRELESS COMM	AT&T INC	AT&T INC
APPLE INC	BROADCOM CORP	BAE SYSTEMS PLC
AT&T INC	HP INC	INTEL CORP
KAPSCH TRAFFICOM AG	HYUNDAI CORP	MOTOROLA SOLUTIONS INC
AVAYA INC	INTEL CORP	NEXTWAVE WIRELESS INC
BLACKBERRY LTD	LINEAR TECHNOLOGY CORP	ORANGE SA
FUJITSU LTD	MOTOROLA SOLUTIONS INC	QUALCOMM INC
INTEL CORP	NORTEL NETWORKS CORP	STMICROELECTRONICS NV
INTERMEC INC	SEEQ TECHNOLOGY INC	TDF CORP
INTL BUSINESS MACHINES CORP	SYNOPTICS COMM INC	
JAPAN RADIO CO LTD	XEROX CORP	
KDDI CORP		
KONINKLIJKE KPN NV		
LUCENT TECHNOLOGIES INC		
MOTOROLA SOLUTIONS INC		
NIPPON TELEGRAPH & TELEPHONE		
NOKIA CORP		
NORAND CORP		
NOVELL INC		
PROXIM CORP		
RENESAS ELECTRONICS CORP		
RSA SECURITY INC		
SHARP CORP		
SONY CORP		
STANDARD MICROSYSTEMS CORP		
SYMBOL TECHNOLOGIES		
TECHNICOLOR SA		
TOSHIBA CORP		
XIRCOM INC		

<sup>7</sup> Not all of these companies have CRSP and Compustat data and, hence, not all of these firms are in our sample.

**Appendix B**  
**Examples of Analyst and Firm Disclosures related to SSO Activity**

*Excerpts from Conference Calls*

---

JULY 17, 2015 / 12:00PM, ERIC B.ST - Q2 2015 Ericsson Earnings Call

Kai Korschelt - BofA Merrill Lynch – Analyst:

“...And then my other question is on the 5G side. **Do you think you are in a good position to at least defend a good market share, in terms of standard essential patents, given that we are still only in the standard setting phase here?** Thank you.”

Hans Vestberg - Telefonaktiebolaget L M Ericsson – CEO

“I start backwards. I start with 5G. And I think we're in a good position. **We're early out, we're part of standardization. I think we have done a lot of innovation already.** We can basically replicate many of the discrete sort of requirements on 5G already, right now. We just need to put it in a little bit smaller phone. Right now, it's a little bit big.”

---

---

JULY 16, 2015 / 4:00PM, CSCO - Cisco Systems Inc Corporate Call - Goldman Sachs to Host Tech Talk With Cisco

Simona Jankowski - Goldman Sachs – Analyst

“So **how do you see all of those standard-setting bodies or consortia coexisting?** And will they actually solve the problem that they've set out to solve?”

Maciej Kranz - Cisco Systems Inc - VP, Corporate Technology Group

“...So the number of standards and standard-like bodies is in the hundreds. And so our approach - and I think an industry approach -- has been, on the one hand, let's make sure that **we focus on a few of these standard bodies and consortia, and organizations, and focus them on specific problems...** So that we take all of these different implementations, and actually do proof of concepts, and make sure that multiple vendors can inter-operate in these environments.”

---

**Appendix B (continued)**  
**Examples of Analyst and Firm Disclosures related to SSO Activity**

*Excerpts from Analyst Research Reports*

---

**Companies:** Broadcom and Marvell

**Publication Date:** 5/14/2015

**Contributor/Analyst:** J.P. Morgan

Research report on Broadcom and Marvell (in the semiconductors sector)

“IEEE Patent Policy Update Could Impact the Connectivity Chipset Landscape in Favor of OW-rated BRCM and MRVL.

...

**We focus on technology standard setting for the connectivity market (i.e., Wi-Fi, Ethernet) and believe that Broadcom and Marvell stand to benefit from this IEEE patent policy update** as one of their major connectivity chipset competitors, Qualcomm, which charges royalties based on system (i.e., smartphone) ASP, plan to limit or remove itself from participation in the IEEE standards setting process. We believe Broadcom and Marvell, who are leaders in the connectivity chipset market and who we believe will adhere to the new patent policy update and continue to contribute intellectual property to the standardization of new Wi-Fi technologies in IEEE, will gain a 6-12 month time-to-market advantage in the connectivity chipset market. We reiterate our OW rating on BRCM and MRVL.”

---

**Company:** Silicon Storage Technology, Inc.

**Publication Date:** 7/17/2013

**Contributor/Analyst:** GLOBALDATA

“Silicon Storage Technology, Inc. - SWOT Analysis

Strength - Certificates and Professional Affiliations

**SST is part of ETSI, the European Telecommunications Standards Institute, which manages the 3GPP Global Initiative.** SST is dedicated to supporting global standards for telecommunications. SST is a member of the American Electronics Association (AeA), a nationwide non-profit trade association. It is an Affiliate Member of OMTP, an operator-sponsored forum that serves the needs of each and every link in the mobile phone value chain by gathering and driving mobile terminal requirements. In addition, the company received ISO 9001:2008 Quality Management System (QMS) certification in November 2010. This QMS certification compliments SST's established reputation for consistently delivering quality products and services that meet or exceed the company's customer's quality and regulatory requirements, while continually improving customer satisfaction and services. Such affiliation and certification further enhance the company's brand image and provide growth opportunities for the company.”

---

**Appendix B (continued)**  
**Examples of Analyst and Firm Disclosures related to SSO Activity**

*Excerpts from 10-K/Qs*

---

COMPANY: IXIA

FORM TYPE: 10-K

DOCUMENT DATE: December 31, 2014, FILING DATE: March 31, 2015, p. 12

**Research and Development**

We believe that research and development is critical to our business. Our development efforts include anticipating and addressing the network performance analysis and monitoring needs of network equipment manufacturers, service providers, enterprises and government customers, and focusing on emerging high growth network technologies.

Our future success depends on our ability to continue to enhance our existing products and to develop new products that address the needs of our customers. We closely monitor changing customer needs by communicating and working directly with our customers, partners and distributors. **We also receive input from our active participation in industry groups responsible for establishing technical standards.**

Development schedules for technology products are inherently difficult to predict, and there can be no assurance that we will introduce any proposed new products in a timely fashion. Also, we cannot be certain that our product development efforts will result in commercially successful products or that our products will not contain software errors or other performance problems or be rendered obsolete by changing technology or new product announcements by other companies.

---

---

COMPANY: SILICON IMAGE INC

FORM TYPE: 10-Q

DOCUMENT DATE: June 30, 2014, FILING DATE: August 8, 2014, p. 46

*Our business may be adversely impacted as a result of the adoption of competing standards and technologies by the broader market.*

**The success of our business to date has depended on our participation in standard setting organizations, such as the HDMI and MHL Consortiums, and the widespread adoption and success of those standards.** From time to time, competing standards have been established which negatively impact the success of existing standards or jeopardize the creation of new standards. DisplayPort is an example of a competing standard on a different technology base which has been created as an alternative high definition connectivity solution in the PC space. The DisplayPort standard has been adopted by many large PC manufacturers. While currently not as widely recognized as the HDMI standard, DisplayPort does represent a viable alternative to the HDMI or MHL technologies. If DisplayPort should gain broader adoption, especially with non-PC consumer electronics, our HDMI or MHL businesses could be negatively impacted and our revenues could be reduced. WiGig is an example of a competing 60GHz standard which has been created as an alternative high-bandwidth wireless connectivity solution for the PC industry. While the WiGig standard has not been in the market as long as the WirelessHD standard, it does represent a viable alternative to WirelessHD for 60GHz connectivity. If WiGig should gain broader adoption before WirelessHD is adopted, it could negatively impact the adoption of WirelessHD.

---

**TABLE 1**  
**Standard Setting Organizations Included in Sample**

SSO Name	Examples of Technology	Number of Firms in SSO	Percent
ATIS: Alliance for Telecommunications Industry Solutions	Wireless networks (4G, 5G)	73	8.6%
ATSC: Advanced Television Systems Committee	Digital television	58	6.8%
CENSA: Collaborative Electronic Notebook Systems Association	eRecords (ELN, XML)	5	0.6%
Digital Versatile Discs (DVD) Forum	DVD	86	10.2%
ETSI: European Telecommunications Standards Institute	Wireless networks (GSM, DECT)	123	14.5%
IEEE: The Institute of Electrical and Electronics Engineers	Computing (WiFi, Bluetooth)	174	20.5%
OASIS: Organization for the Advancement of Structured Information Standards	Internet (SAML, CAMP)	90	10.6%
TIA: Telecommunications Industry Association	Telecom (Radio, Fiber optics)	166	19.6%
WFMC: Workflow Management Coalition	Digital workflow (XPDL, BPM)	<u>72</u>	8.5%
		847	

This table shows that nine Standard Setting Organizations (SSOs) for which we obtained data from the Searle Center on Law, Regulation, and Economic Growth at Northwestern University. The number of firms represents only companies that are in the CRSP-Compustat universe. Private firms and other participants (e.g. universities) are not included in the totals. Some firms belong to more than one SSO so the total number of firms does not represent the number of unique firms in the sample.

**TABLE 2**  
**Treatment Sample of First-Time SSO-Contributing Firms**

*Panel A: Selection of Treatment Sample*

Number of Unique Participating SSO firms	550
Less Passive Participants only	<u>(247)</u>
Number of First-Time Committee Participants	253
Less Firms Not in CRSP-Compustat	<u>(108)</u>
Number of First-Time Committee Participants in CRSP-Compustat	145
Less Missing Values of PSM Model Variables	<u>(26)</u>
Number of Treatment firms in PSM model	119

*Panel B: First-Time Committee Contributions by Year*

Year	Number	Percent
1990	4	3.4%
1992	1	0.8%
1993	7	5.9%
1994	2	1.7%
1995	11	9.2%
1996	4	3.4%
1997	21	17.6%
1998	6	5.0%
1999	6	5.0%
2000	3	2.5%
2001	9	7.6%
2002	5	4.2%
2003	6	5.0%
2004	5	4.2%
2005	5	4.2%
2006	3	2.5%
2007	3	2.5%
2008	4	3.4%
2009	3	2.5%
2010	1	0.8%
2011	2	1.7%
2012	4	3.4%
2013	2	1.7%
2014	<u>2</u>	1.7%
Total	119	

**TABLE 2 (continued)**  
**Treatment Sample of First-Time SSO-Contributing Firms**

*Panel C: First-Time Committee Contributions by Industry*

2-digit SIC	Industry Description	Number	Percent
23	APPAREL AND OTHER FINISHED PRODUCTS MADE FROM FABRICS AND SIMILAR MATERIAL	1	0.8%
26	PAPER AND ALLIED PRODUCTS	1	0.8%
27	PRINTING, PUBLISHING, AND ALLIED INDUSTRIES	1	0.8%
28	CHEMICALS AND ALLIED PRODUCTS	6	5.0%
32	STONE, CLAY, GLASS, AND CONCRETE PRODUCTS	2	1.7%
33	PRIMARY METAL INDUSTRIES	3	2.5%
35	INDUSTRIAL AND COMMERCIAL MACHINERY AND COMPUTER EQUIPMENT	18	15.1%
36	ELECTRONIC AND OTHER ELECTRICAL EQUIPMENT AND COMPONENTS, EXCEPT COMPUTER	41	34.5%
37	TRANSPORTATION EQUIPMENT	6	5.0%
38	MEASURING, ANALYZING & CONTROLLING INSTRUMENTS; PHOTOGRAPHIC, MEDICAL & OPTICAL GOODS; WATCHES & CLOCKS	5	4.2%
39	MISCELLANEOUS MANUFACTURING INDUSTRIES	1	0.8%
48	COMMUNICATIONS	11	9.2%
49	ELECTRIC, GAS, AND SANITARY SERVICES	1	0.8%
50	WHOLESALE TRADE & DURABLE GOODS	2	1.7%
60	DEPOSITORY INSTITUTIONS	1	0.8%
67	HOLDING AND OTHER INVESTMENT OFFICES	1	0.8%
73	BUSINESS SERVICES	17	14.3%
87	ENGINEERING, ACCOUNTING, RESEARCH, MANAGEMENT, AND RELATED SERVICES	<u>1</u>	0.8%
	Total	119	

The table describes the treatment sample, which is comprised of firms that commence active contributions to an SSO committee. Panel A shows the number of unique firms, the number of firms that actively contribute to a committee, and the number of active contributing firms with the required data to join our treatment sample. We identify the treatment year as the first time a treatment firm makes a contribution to any SSO committee. Panel B shows the number of treatment years by calendar year. Panel C shows the two-digit SIC membership of the treatment firms.

**TABLE 3**  
**Propensity-Score Matching Model**

*Panel A: Propensity Score Matching Regression*

	Treatment Firm
<i>Ln (Assets)</i>	0.294*** (4.54)
<i>R&amp;D / Assets</i>	3.235*** (2.70)
<i>ROA</i>	1.329 (1.56)
<i>Book / Market</i>	0.055 (0.23)
<i>Sales Growth</i>	0.484** (2.30)
Observations	1,191
Pseudo R-Square	0.059

\*\*\*, \*\*, \* Significantly different from zero at the 0.01, 0.05, 0.10 level, respectively, using a two-tailed test

*Panel B: Descriptive Statistics and Tests of Covariate Balance*

	Treatment Firm-Years					Control Firm-Years					P-value diff in means
	Mean	Std Dev	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	Mean	Std Dev	25 <sup>th</sup>	50 <sup>th</sup>	75 <sup>th</sup>	
<i>Firm Characteristics in PSM Regression</i>											
<i>Ln (Assets)</i>	8.06	2.34	6.42	8.38	9.99	7.70	2.25	6.11	7.90	9.45	0.20
<i>R&amp;D / Assets</i>	0.09	0.10	0.03	0.06	0.13	0.10	0.10	0.02	0.07	0.14	0.80
<i>ROA</i>	0.10	0.21	0.05	0.11	0.21	0.13	0.15	0.05	0.12	0.19	0.32
<i>Book / Market</i>	0.45	0.37	0.21	0.35	0.61	0.45	0.37	0.21	0.37	0.62	0.92
<i>Sales Growth</i>	0.23	0.79	-0.07	0.06	0.24	0.22	0.56	0.00	0.13	0.25	0.85
<i>Other Firm Characteristics</i>											
<i>Return Volatility</i>	0.53	0.31	0.27	0.44	0.75	0.58	0.32	0.35	0.47	0.76	0.20
<i>Sales Guidance</i>	0.28	0.45	0.00	0.00	1.00	0.34	0.47	0.00	0.00	1.00	0.35
<i>EPS Guidance</i>	0.43	0.50	0.00	0.00	1.00	0.42	0.50	0.00	0.00	1.00	0.89
<i>Cash / Assets</i>	0.24	0.21	0.08	0.17	0.34	0.25	0.20	0.08	0.20	0.38	0.60
<i>Debt / Assets</i>	0.16	0.16	0.00	0.13	0.29	0.18	0.20	0.01	0.13	0.27	0.39
<i>Capex / Assets</i>	0.05	0.04	0.02	0.04	0.07	0.06	0.05	0.02	0.05	0.09	0.14
<i>Firm Age</i>	2.60	1.05	1.70	2.71	3.31	2.42	0.95	1.61	2.56	3.14	0.15
<i>Ln (Market Cap)</i>	7.29	2.20	5.39	7.46	9.33	7.44	2.00	5.98	7.80	8.99	0.58
<i>Ln (# Patents)</i>	3.70	2.79	1.10	3.78	6.20	3.02	2.62	0.00	3.09	5.30	0.06

Panel A shows the results of firm-year logistic regressions of an indicator variable for treatment firms (see Table 2) on the determinants of first-time SSO committee contributions. We use fitted values from these regressions as propensity scores to draw three control firm-years for each treated firm-year based on nearest-neighbor matching. Control firm-years are drawn from the subsample of non-contributing firm-years that participate in SSOs during the same calendar year as treatment firm-years. T-statistics are based on standard errors clustered by firm and appear in parentheses below the coefficients. Panel B presents descriptive statistics and tests of covariate balance for the propensity score matched sample. Firm characteristics are measured for the year prior to the treatment year (i.e., first-time committee contribution) or placebo event (for control firms). The sample size is 88 for treatment firms and 227 for control firms, except for *Ln(# Patents)*, where the sample sizes are 58 and 179, respectively.

**TABLE 4**  
**Descriptive Statistics on Forecast Variables**

*Panel A: Management Forecast issuance and frequency*

	All Forecasts	Annual Forecasts	Quarterly Forecasts
	Mean	Mean	Mean
<i>Sales Forecaster</i>	0.458	0.223	0.383
<i>EPS Forecaster</i>	0.472	0.237	0.389
<i>Sales Forecast Freq</i>	2.364	0.804	1.560
<i>EPS Forecast Freq</i>	2.279	0.892	1.387

*Panel B: Management Forecast Properties*

	Annual Forecasts				Quarterly Forecasts			
	Mean	Std Dev	50 <sup>th</sup>	N	Mean	Std Dev	50 <sup>th</sup>	N
<i>Sales Abs(Error)</i>	0.058	0.095	0.027	730	0.060	0.088	0.040	1418
<i>EPS Abs(Error)</i>	0.011	0.015	0.005	799	0.005	0.009	0.002	1224
<i>Sales Bias</i>	0.010	0.095	0.015	730	0.034	0.068	0.032	1418
<i>EPS Bias</i>	0.001	0.017	0.002	799	0.002	0.007	0.001	1224
<i>Sales News</i>	-0.020	0.064	-0.012	618	-0.040	0.198	-0.020	1193
<i>EPS News</i>	-0.003	0.007	-0.001	619	-0.004	0.010	-0.001	923

*Panel C: Analyst Forecast Dispersion*

	Annual Forecasts				Quarterly Forecasts			
	Mean	Std Dev	50 <sup>th</sup>	N	Mean	Std Dev	50 <sup>th</sup>	N
<i>Sales Dispersion</i>	0.026	0.043	0.013	7277	0.023	0.034	0.013	6074
<i>EPS Dispersion</i>	0.008	0.023	0.003	8522	0.002	0.006	0.001	7392

Panel A presents descriptive statistics on management forecast issuance and frequency variables, which are measured at the firm-year level. *EPS Forecaster* (*Sales Forecaster*) is an indicator variable for management earnings (sales) forecasts in a given year. *EPS Forecast Freq* (*Sales Forecast Freq*) is the frequency of management earnings (sales) forecasts per year. Panel B presents the management forecast property variables, which are measured at the forecast level. *EPS Abs(Error)* (*Sales Abs(Error)*) is the unsigned difference between actual EPS (sales) and the management forecast of EPS (sales), scaled by share price (actual sales). *EPS Bias* (*Sales Bias*) is the signed difference between actual EPS (sales) and the management forecast of EPS (sales), scaled by share price (actual sales). *EPS News* (*Sales News*) is the signed difference between the management forecast of EPS (sales) and the analyst consensus forecast of EPS (sales) at the time of the forecast, scaled by share price (actual sales). Panel C presents analyst forecast dispersion variable, which are measured at the firm-month level. *EPS Dispersion* (*Sales Dispersion*) is the standard deviation of all EPS (sales) forecasts provided by unique analysts in a given firm-month, scaled by share price (actual sales). We require at least two forecasts to compute the dispersion measures.

**TABLE 5**  
**SSO Committee Participation and Management Guidance Frequency**

*Panel A: Dependent Variable: Sales Forecaster*

	All Forecasts		Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Treatment</i>	-0.061 (-0.75)	-0.101 (-1.20)	-0.148* (-1.94)	-0.147** (-2.07)	0.005 (0.06)	-0.013 (-0.15)
<i>Post</i>	-0.054* (-1.94)	-0.071** (-2.54)	-0.051* (-1.81)	-0.057* (-1.89)	-0.031 (-0.93)	-0.039 (-1.13)
<i>Treatment * Post</i>	0.169** (1.98)	0.207** (2.33)	0.165* (1.97)	0.169* (1.89)	0.104 (1.20)	0.126 (1.40)
<i>Ln (Assets)</i>	-0.030* (-1.70)	-0.050** (-2.08)	0.002 (0.17)	-0.030* (-1.90)	-0.029 (-1.62)	-0.026 (-1.05)
<i>Ln (# Patents)</i>		0.029 (1.64)		0.037** (2.45)		0.011 (0.60)
<i>Return Volatility</i>		-0.049 (-0.41)		-0.121 (-1.22)		0.128 (1.00)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	909	843	909	843	909	843
Adjusted R-Square	0.516	0.519	0.241	0.264	0.421	0.406

*Panel B: Dependent Variable: EPS Forecaster*

	All Forecasts		Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Treatment</i>	-0.002 (-0.02)	-0.055 (-0.55)	-0.118 (-1.32)	-0.121 (-1.38)	0.083 (0.88)	0.051 (0.52)
<i>Post</i>	-0.091** (-2.48)	-0.117*** (-3.10)	-0.056* (-1.82)	-0.067** (-2.23)	-0.071* (-1.85)	-0.087** (-2.14)
<i>Treatment * Post</i>	-0.038 (-0.40)	-0.013 (-0.14)	0.061 (0.87)	0.054 (0.75)	-0.079 (-0.86)	-0.070 (-0.73)
<i>Ln (Assets)</i>	0.004 (0.18)	-0.031 (-0.97)	0.019 (1.23)	-0.030 (-1.53)	-0.002 (-0.08)	-0.009 (-0.30)
<i>Ln (# Patents)</i>		0.032 (1.61)		0.026 (1.53)		0.014 (0.72)
<i>Return Volatility</i>		-0.311** (-2.13)		-0.483*** (-3.29)		-0.046 (-0.32)
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	909	843	909	843	909	843
Adjusted R-Square	0.162	0.192	0.0822	0.142	0.129	0.124

\*\*\*, \*\*, \* Significantly different from zero at the 0.01, 0.05, 0.10 level, respectively, using a two-tailed test

Panel A (Panel B) presents results of OLS regressions with *Sales Forecaster* (*EPS Forecaster*)—an indicator for a sales (EPS) forecast in a firm-year—as the dependent variable. *Treatment* = 1 for firms that contribute to SSO committees and *Treatment* = 0 for firms that do not. For each treatment (control) firm, we keep the three years prior to the treatment (placebo) year, where *Post*=0, and three years subsequent, where *Post*=1. *Treatment \* Post* measures whether the change from before to after the treatment or placebo year is significantly different between treatment firms and control firms. Other variables are defined in Table 3. T-statistics are based on standard errors clustered by firm and appear in parentheses below the coefficients.

**TABLE 6**  
**SSO Committee Participation and Management Guidance Accuracy**

*Panel A: Dependent Variable: Sales Abs(Error)*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	0.060*** (3.22)	0.054** (2.58)	-0.009 (-0.95)	-0.011 (-1.03)
<i>Post</i>	-0.006 (-0.85)	-0.007 (-0.87)	-0.011* (-1.69)	-0.012 (-1.60)
<i>Treatment * Post</i>	-0.061** (-2.61)	-0.065** (-2.54)	0.001 (0.09)	0.002 (0.14)
<i>Ln (Assets)</i>	-0.010** (-2.12)	-0.008* (-1.99)	-0.002 (-0.96)	-0.001 (-0.27)
<i>Forecast Revision</i>	-0.033*** (-3.64)	-0.039*** (-4.23)	-0.019** (-2.42)	-0.018** (-2.07)
<i>Ln (# Patents)</i>		0.003 (0.84)		-0.001 (-0.21)
<i>Return Volatility</i>		0.043 (0.88)		0.000 (0.01)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	730	622	1,418	1,252
Adjusted R-Square	0.283	0.318	0.215	0.206
Post Diff P-value	0.928	0.434	0.367	0.385

*Panel B: Dependent Variable: EPS Abs(Error)*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	0.009*** (3.01)	0.005** (2.04)	0.002 (1.47)	0.002 (1.22)
<i>Post</i>	-0.000 (-0.22)	-0.001 (-1.39)	-0.000 (-0.14)	0.000 (0.08)
<i>Treatment * Post</i>	-0.006** (-2.14)	-0.005* (-1.97)	-0.003* (-1.83)	-0.003* (-1.67)
<i>Ln (Assets)</i>	-0.002* (-1.85)	-0.003*** (-2.89)	-0.002*** (-2.92)	-0.002** (-2.61)
<i>Forecast Revision</i>	-0.006*** (-3.57)	-0.007*** (-3.84)	-0.001 (-1.60)	-0.001 (-1.54)
<i>Ln (# Patents)</i>		0.002*** (2.84)		0.000 (0.36)
<i>Return Volatility</i>		0.017* (1.96)		0.006 (0.92)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	799	719	1,224	1,119
Adjusted R-Square	0.205	0.255	0.104	0.113
Post Diff P-value	0.370	0.990	0.248	0.198

\*\*\*, \*\*, \* Significantly different from zero at the 0.01, 0.05, 0.10 level, respectively, using a two-tailed test

**TABLE 6 (continued)**  
**SSO Committee Participation and Management Guidance Accuracy**

Panel A (Panel B) presents results of OLS regressions with *Sales Abs(Error)* (*EPS Abs(Error)*)—the unsigned difference between actual sales (EPS) and management forecast of sales (EPS), scaled by sales (price)—as the dependent variable. *Treatment* = 1 for firms that contribute to SSO committees and *Treatment* = 0 for firms that do not. For each treatment (control) firm, we keep the three years prior to the treatment (placebo) year, where *Post*=0, and three years subsequent, where *Post*=1. *Treatment \* Post* measures whether the change from before to after the treatment or placebo year is significantly different between treatment firms and control firms. *Forecast Revision* is an indicator variable that is equal to one for management forecasts that are a revision of a prior forecast and equal to zero for initial forecasts. Other variables are defined in Table 3. T-statistics are based on standard errors clustered by firm and appear in parentheses below the coefficients. Post Diff P-value is a *p*-value for the test *Treatment + Treatment \* Post* = 0; i.e., whether the post-treatment level of the variable for treatment firms is significantly different than the pre-level for control firms.

**TABLE 7**  
**SSO Committee Participation and Management Guidance Bias**

*Panel A: Dependent Variable: Sales Bias*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	-0.096*** (-3.37)	-0.096*** (-3.42)	-0.016** (-2.00)	-0.023*** (-2.79)
<i>Post</i>	-0.009 (-0.84)	-0.009 (-0.82)	-0.009* (-1.84)	-0.008 (-1.43)
<i>Treatment * Post</i>	0.110*** (3.41)	0.106*** (3.33)	0.021** (2.16)	0.028*** (2.94)
<i>Ln (Assets)</i>	-0.003 (-0.53)	-0.008 (-1.02)	-0.001 (-0.44)	-0.002 (-0.45)
<i>Forecast Revision</i>	-0.013 (-1.43)	-0.014 (-1.38)	-0.007 (-1.61)	-0.007 (-1.41)
<i>Ln (# Patents)</i>		0.002 (0.52)		0.001 (0.35)
<i>Return Volatility</i>		-0.023 (-0.83)		-0.000 (-0.00)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	730	622	1,418	1,252
Adjusted R-Square	0.158	0.166	0.0903	0.092
Post Diff P-value	0.572	0.689	0.495	0.610

*Panel B: Dependent Variable: EPS Bias*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	-0.008** (-2.06)	-0.012** (-2.53)	0.001 (0.97)	0.001 (0.93)
<i>Post</i>	0.002 (0.88)	0.001 (0.66)	0.000 (0.10)	0.000 (0.60)
<i>Treatment * Post</i>	0.002 (0.38)	0.003 (0.43)	-0.002 (-1.35)	-0.002 (-1.50)
<i>Ln (Assets)</i>	0.001 (0.98)	-0.001 (-0.71)	-0.000 (-0.55)	-0.000 (-0.63)
<i>Forecast Revision</i>	-0.002 (-1.56)	-0.003* (-1.99)	-0.001 (-1.58)	-0.001 (-1.49)
<i>Ln (# Patents)</i>		0.002*** (2.73)		0.001 (1.42)
<i>Return Volatility</i>		0.002 (0.14)		0.007* (1.85)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	799	719	1,224	1,119
Adjusted R-Square	0.193	0.221	0.071	0.100
Post Diff P-value	0.421	0.230	0.267	0.128

\*\*\*, \*\*, \* Significantly different from zero at the 0.01, 0.05, 0.10 level, respectively, using a two-tailed test

**TABLE 7 (continued)**  
**SSO Committee Participation and Management Guidance Bias**

Panel A (Panel B) presents results of OLS regressions with *Sales Bias (EPS Bias)*—the signed difference between actual sales (EPS) and management forecast of sales (EPS), scaled by sales (price)—as the dependent variable. *Treatment* = 1 for firms that contribute to SSO committees and *Treatment* = 0 for firms that do not. For each treatment (control) firm, we keep the three years prior to the treatment (placebo) year, where *Post*=0, and three years subsequent, where *Post*=1. *Treatment \* Post* measures whether the change from before to after the treatment or placebo year is significantly different between treatment firms and control firms. *Forecast Revision* is an indicator variable that is equal to one for management forecasts that are a revision of a prior forecast and equal to zero for initial forecasts. Other variables are defined in Table 3. T-statistics are based on standard errors clustered by firm and appear in parentheses below the coefficients. Post Diff P-value is a *p*-value for the test  $Treatment + Treatment * Post = 0$ ; i.e., whether the post-treatment level of the variable for treatment firms is significantly different than the pre-level for control firms.

**TABLE 8**  
**SSO Committee Participation and Management Guidance News**

*Panel A: Dependent Variable: Sales News*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	-0.043** (-2.48)	-0.043** (-2.49)	-0.032*** (-3.02)	-0.036** (-2.39)
<i>Post</i>	-0.004 (-0.58)	-0.004 (-0.62)	-0.005 (-0.61)	-0.010 (-1.22)
<i>Treatment * Post</i>	0.038** (2.14)	0.042** (2.12)	0.031 (1.50)	0.038 (1.48)
<i>Ln (Assets)</i>	0.011** (2.35)	0.012* (1.95)	0.019** (2.16)	0.018* (1.79)
<i>Forecast Revision</i>	0.013 (1.43)	0.014 (1.37)	0.003 (0.30)	0.004 (0.30)
<i>Ln (# Patents)</i>		-0.003 (-1.57)		-0.007 (-1.08)
<i>Return Volatility</i>		-0.059** (-2.35)		-0.117* (-1.72)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	618	513	1,193	1,028
Adjusted R-Square	0.155	0.178	0.028	0.036
Post Diff P-value	0.736	0.919	0.959	0.919

*Panel B: Dependent Variable: EPS News*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	-0.003** (-2.19)	-0.002 (-1.47)	-0.003* (-1.84)	-0.004 (-1.64)
<i>Post</i>	-0.000 (-0.69)	-0.000 (-0.49)	-0.000 (-0.43)	-0.001 (-0.60)
<i>Treatment * Post</i>	0.002 (1.40)	0.001 (0.89)	0.004* (1.96)	0.004 (1.46)
<i>Ln (Assets)</i>	0.001 (1.31)	0.001** (2.07)	0.002*** (3.09)	0.002** (2.12)
<i>Forecast Revision</i>	0.003*** (3.11)	0.004*** (3.36)	-0.001 (-0.46)	-0.001 (-0.62)
<i>Ln (# Patents)</i>		-0.001** (-2.43)		0.000 (0.35)
<i>Return Volatility</i>		0.002 (0.53)		-0.006 (-0.78)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	619	540	923	818
Adjusted R-Square	0.172	0.158	0.117	0.122
Post Diff P-value	0.307	0.609	0.370	0.946

\*\*\*, \*\*, \* Significantly different from zero at the 0.01, 0.05, 0.10 level, respectively, using a two-tailed test

**TABLE 8 (continued)**  
**SSO Committee Participation and Management Guidance News**

Panel A (Panel B) presents results of OLS regressions with *Sales News* (*EPS News*)—the signed difference between management forecast of sales (EPS) and the outstanding analyst consensus forecast of sales (price), scaled by sales (price)—as the dependent variable. *Treatment* = 1 for firms that contribute to SSO committees and *Treatment* = 0 for firms that do not. For each treatment (control) firm, we keep the three years prior to the treatment (placebo) year, where *Post*=0, and three years subsequent, where *Post*=1. *Treatment* \* *Post* measures whether the change from before to after the treatment or placebo year is significantly different between treatment firms and control firms. *Forecast Revision* is an indicator variable that is equal to one for management forecasts that are a revision of a prior forecast and equal to zero for initial forecasts. Other variables are defined in Table 3. T-statistics are based on standard errors clustered by firm and appear in parentheses below the coefficients. Post Diff P-value is a *p*-value for the test  $Treatment + Treatment * Post = 0$ ; i.e., whether the post-treatment level of the variable for treatment firms is significantly different than the pre-level for control firms.

**TABLE 9**  
**SSO Committee Participation and Analyst Forecast Dispersion**

*Panel A: Dependent Variable: Sales Dispersion*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	-0.003 (-1.04)	-0.005 (-1.47)	-0.002 (-0.51)	-0.001 (-0.30)
<i>Post</i>	-0.004** (-2.12)	-0.003 (-1.59)	-0.002 (-1.09)	-0.001 (-0.52)
<i>Treatment * Post</i>	0.010 (1.57)	0.010 (1.66)	0.001 (0.16)	0.000 (-0.02)
<i>Ln (Assets)</i>	-0.001 (-1.22)	0.000 (-0.18)	-0.001 (-1.65)	-0.002* (-1.75)
<i>Ln (# Patents)</i>		0.000 (-0.03)		0.001 (0.97)
<i>Return Volatility</i>		0.020** (2.11)		0.011 (1.46)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	7,277	6,562	6,074	5,417
Adjusted R-Square	0.110	0.130	0.100	0.110
Post Diff P-value	0.255	0.330	0.662	0.652

*Panel B: Dependent Variable: EPS Dispersion*

	Annual Forecasts		Quarterly Forecasts	
	(1)	(2)	(3)	(4)
<i>Treatment</i>	0.001 (0.44)	0.000 (0.18)	0.000 (0.47)	0.000 (0.37)
<i>Post</i>	-0.000 (-0.23)	-0.000 (-0.10)	0.000 (0.03)	0.000 (0.00)
<i>Treatment * Post</i>	-0.004* (-1.77)	-0.004* (-1.86)	-0.001* (-1.77)	-0.001 (-1.62)
<i>Ln (Assets)</i>	-0.002*** (-2.72)	-0.000 (-0.24)	-0.001*** (-2.95)	-0.000 (-1.59)
<i>Ln (# Patents)</i>		-0.000 (-0.16)		0.000 (0.14)
<i>Return Volatility</i>		0.028* (1.76)		0.007* (1.77)
Industry and Year FE	Yes	Yes	Yes	Yes
Observations	8,522	7,815	7,392	6,735
Adjusted R-Square	0.082	0.118	0.107	0.124
Post Diff P-value	0.106	0.074	0.169	0.223

\*\*\*, \*\*, \* Significantly different from zero at the 0.01, 0.05, 0.10 level, respectively, using a two-tailed test

**TABLE 9 (continued)**  
**SSO Committee Participation and Analyst Forecast Dispersion**

Panel A (Panel B) presents results of OLS regressions with *Sales Dispersion (EPS Dispersion)*—the firm-month standard deviation of analysts' forecasts of sales (EPS), scaled by sales (price)—as the dependent variable. *Treatment* = 1 for firms that contribute to SSO committees and *Treatment* = 0 for firms that do not. For each treatment (control) firm, we keep the three years prior to the treatment (placebo) year, where *Post*=0, and three years subsequent, where *Post*=1. *Treatment \* Post* measures whether the change from before to after the treatment or placebo year is significantly different between treatment firms and control firms. Other variables are defined in Table 3. T-statistics are based on standard errors clustered by firm and appear in parentheses below the coefficients. Post Diff P-value is a *p*-value for the test  $Treatment + Treatment * Post = 0$ ; i.e., whether the post-treatment level of the variable for treatment firms is significantly different than the pre-level for control firms.