

Working Paper 21-085

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The researchers obtained human subjects research approval from their universities to conduct this study. Furthermore, the participating universities signed a data usage agreement with the participating company, compliant with the General Data Protection Regulation of the European Union. The agreement specifies the research team members who can access the data. We also thank the grocery store chain company for agreeing to collaborate with us on this field experiment, supporting us with the development of this project, and providing us with access to data.

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# Effects of Structured Sharing of Best Practices in an Unstructured Information Sharing System

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## Abstract

Unstructured information sharing systems, such as certain enterprise social networks (ESNs), can supplement top-down knowledge transfer with a wide array of ideas through peer-to-peer knowledge sharing. However, the unstructured nature of such systems can also lead to information overload and difficulty in finding useful information. We examine data from a natural field experiment where a retailer introduced *structured sharing of best practices* (SSBP) in an existing ESN, a control mechanism to encourage certain high-performing units to share best practices using a clear structure. The SSBP significantly increased the sales trends of the stores where it was implemented. Sales improvement was greatest in stores that (a) perceived higher ESN information overload before the intervention, (b) had lower *ex-ante* exposure to relevant knowledge, or (c) were exposed to higher-quality posts during the intervention, and was lowest in stores serving markets differing from those served by the best-practices stores. The SSBP also led to an increase of voluntary inter-store knowledge sharing. These findings shed light on how structured information sharing in an unstructured system can enhance the decision-facilitating role of relevant information without discouraging unstructured peer-to-peer knowledge sharing.

The researchers obtained human subjects research approval from their universities to conduct this study. Furthermore, the participating universities signed a data usage agreement with the participating company, compliant with the General Data Protection Regulation of the European Union. The agreement specifies the research team members who can access the data. We thank Evelina Forker and seminar participants at Arizona State University, Carnegie Mellon, the University of North Carolina, the University of Pennsylvania, and the University of Southern California, as well as participants at the 2020 Consortium for Operational Excellence in Retailing at Harvard Business School and the 2021 Management Accounting Section of the American Accounting Association's Midyear Meeting for helpful comments. We thank Lydia Chew, Lene Furuseth, Victoria Liublinska Prince, Trang Nguyen, Christine Rivera, and Andrea Wetzler for excellent research assistance throughout the project. We also thank the grocery store chain company for agreeing to collaborate with us on this field experiment, supporting us with the development of this project, and providing us with access to data. All errors are our own.

## I. INTRODUCTION

Companies have increasingly adopted unstructured information sharing systems (such as certain enterprise social networks), in large part to encourage employees to easily share knowledge on how to better do their work. These systems enable peer-to-peer spontaneous knowledge sharing, imposing few restrictions on what can be shared, when, how, and by whom. However, while the *unstructured* nature of these systems invites employees to share a broad array of ideas (Huang, Singh, and Ghose 2015), it can also limit knowledge-sharing effectiveness. Extensive idea sharing could result in information overload and/or the sharing of low-quality ideas, making it hard to distinguish high- and low-quality information and potentially reducing the credibility of all knowledge shared through the system (Levine and Prietula 2012). The use of unstructured information systems in recent decades, including blogs and ESNs, has been identified as a significant source of information overload (Bawden and Robinson 2009, Chen and Wei 2019). Thus, many organizations and scholars are now advocating for structured mechanisms to facilitate the sharing of useful knowledge, such as best practices, within these unstructured systems (Oleson 2013; Charki, Boukef, and Harrison 2018).

Using a natural field experiment, we examine whether and when introducing a structure for sharing best practices in an unstructured information sharing system can lead to more productive knowledge sharing, reflected by a higher rate of improvement in financial performance. We define “*structured sharing of best practices in an unstructured information sharing system*” (hereafter, SSBP) as a management control mechanism encouraging certain high-performing units to share best practices. This involves linking certain knowledge shared in an unstructured information sharing system to a high-quality source and making the information available at a predictable time

and location within the system, without limiting unstructured information sharing elsewhere in the system. By *best practices* we mean “internal practices...performed in a superior way in some part of the organization and ... deemed superior to internal alternate practices and known alternatives outside the company” (Szulanski 1996: 28).

Without structure, users of an unstructured system might share best practices in a haphazard way. They might share fragments of best practices - such as details of actions taken or results achieved - at any time or in any group within the system, making it hard for others to identify which posts are from high performers and which practices are reliable. When an unstructured system already has high information volume (e.g., from social interactions, announcements, and the accumulation of past information), scattered best practices become very difficult to find, trust, and use. SSBP can solve this problem by allowing users to know where and when to find best practices in a given category. SSBP can limit the downside costs of searching for information in an unstructured information system (Oleson 2013; Charki, Boukef, and Harrison 2018) by directing employee attention to high-quality information (O’Leary 2007; Sandino 2019). It can also encourage high-performing units to post information in the system by providing a credible channel to share ideas. However, SSBP may also unintentionally drive attention away from other spontaneously shared ideas in the system which might be more applicable to a particular learning unit.

SSBP’s effectiveness may depend on factors described in Figure 1. We conjecture that units whose employees experience higher costs of finding relevant information - due to greater information overload in the unstructured system or lower exposure to a network of nearby peers or competent managers who may help them identify best practices - are more likely to benefit from the intervention. We also predict that this effect is more likely to lead to greater financial improvement if the shared best-practices information is seen as high-quality. We expect the intervention to be

less effective for units working in markets differing from those generally served by the sharing units (hereafter referred to as best practices or BP units). SSBP could also discourage employees in units not chosen as BP units from spontaneously sharing useful content, as they might perceive that only certain types of ideas or ideas from certain users are valued in the system.

We test our hypotheses using data from a large European chain of franchise-operated grocery stores that implemented an SSBP intervention in some stores. The company already shared best practices via top-down methods (e.g., operating guidelines and training workshops). It also used an unstructured enterprise social network (hereafter, ESN) similar to Facebook that enabled employees to develop groups, share ideas, and engage in discussions as they saw fit. However, the unstructured ESN was overloaded with information from employee groups, including hundreds of monthly posts within many of those groups. The SSBP intervention was a natural field experiment that involved 587 stores in 11 regions. The treatment group comprised 274 stores in five randomly selected regions. The control group was 313 stores in six control regions. In the ESN with overflowing information, the treatment involved submitting only two posts - every month, in each regional group of the ESN - featuring best practices from two BP units in that region, using a clear structure (i.e., describing best practices with pictures and words, linking actions to results attained by high performers, and organizing best practices by product categories). This intervention was not implemented in the control regions.

We examine changes in the sales performance improvement of the treated stores relative to changes in the control stores. Although we observe no immediate improvement in sales, we find the intervention associated with a 3.67-percent increase in the sales trend of the treatment group relative to the control group by the end of the 18-week intervention. The effect was stronger for stores whose employees reacted more to the best practices posts (hereafter, BP posts).

In assessing the conditions that moderated the effects of the SSBP, we find more positive effects in stores where, *prior to the intervention*, employees perceived an overload of information in the ESN or had lower exposure to best-practices knowledge (measured based on the store's lack of exposure to other same-company stores and the store staff's lack of trust in their regional manager's competence). These results are consistent with the notion that the SSBP reduced employees' cost of finding useful information. Further confirming this interpretation, we find more positive effects where the quality of information shared through the SSBP was seen as higher. On the other hand, we also find that SSBP was less effective in units serving different markets than the ones served by the BP units. This means that the intervention might have caused non-BP units to fixate on the limited set of practices featured by SSBP, even if those ideas did not apply to them and other - possibly more helpful - ideas were available elsewhere in the system. We also examined the possibility that SSBP discouraged employees of non-BP units from posting, though our analyses revealed the opposite effect: SSBP *increased* knowledge sharing between units. Overall, these results suggest that SSBP can improve sales trends and promote knowledge sharing but may also lead employees to focus narrowly on certain ideas, which may be detrimental for units operating in divergent markets.

Our study contributes to an emerging literature in accounting, information systems, and management examining the effects of unstructured information sharing systems (including various ESNs) on learning and performance. Studies have suggested that the unstructured and broad-based nature of ESNs can explain successful knowledge sharing. For example, Huang, Singh, and Ghose (2015) and Neeley and Leonardi (2018) found broad-based non-work information sharing driving employees' interest and trust in each other, resulting in greater knowledge sharing and organizational learning. However, other studies suggest that the lack of structure and the broad

exposure to ideas in an ESN can create information overload (Chen and Wei 2019). Our study sheds light on whether structured knowledge sharing within an unstructured information sharing system increases learning and performance trends by reducing the costs of finding relevant information or whether it has the opposite effect by driving employee attention away the wide array of ideas posted by their peers. Our results generally support the notion that SSBP can improve learning and sales trends without discouraging unstructured knowledge sharing, but we also find conditions in which the benefits to financial results are limited.

More broadly, we contribute to the accounting literature on using management control systems as decision-facilitating tools, directing employee attention to information that could improve decisions and performance (Demski and Feltham 1976). Casas-Arce, Lourenco, and Martinez-Jerez (2017) and Anderson and Kimball (2019) find evidence that greater use of information from performance measurement systems affects decision-making and performance outcomes, while Li and Sandino (2018) find that an information sharing system designed to record creative work led to greater employee engagement and creativity in units with greater need for innovative ideas. However, Eppler and Mengis (2004) and Casas-Arce et al. (2017) highlight a potential challenge with exposing employees to systems containing overly detailed information—such systems could degrade performance through information overload. The tendency to expose employees to increasingly detailed information (prompted by increased use of “big data” and information sharing systems) calls for management control systems that reduce the costs of finding and processing valuable information. We shed light on the extent to which SSBP mechanisms within unstructured or broad-based information-sharing systems can enhance the decision-facilitating role of relevant information in our new world of (over)abundant information.



Finally, our study sheds light on ways to leverage enterprise information sharing systems to increase productive employee interactions and exchange of ideas, especially in the face of increasing information overload from such systems, a topic of great interest to managers and entrepreneurs. To the best of our knowledge, our study is the first to examine whether SSBP mechanisms can enhance knowledge sharing across units and improve financial performance trends. The rest of the paper is organized as follows: Section II presents our hypothesis development. Section III describes the research setting and intervention. Section IV presents our analyses. Section V concludes.

## **II. HYPOTHESIS DEVELOPMENT**

### **2.1. Effects of Structured Sharing of Best Practices in an Unstructured Information Sharing System**

Despite the increasing popularity of information sharing systems such as ESNs, many companies fail to capitalize on their benefits (Leonardi et al. 2013; Charki, Boukef, and Harrison 2018; Neeley and Leonardi 2018; Chin et al. 2020).<sup>1</sup> Many of these information systems are unstructured and broad-based, i.e., they enable any user to share information at any time or “location,” to include any content, and to display that content in any format and group in the system. The varying quality of the information supplied and the high costs of searching for relevant information can limit the benefits of unstructured information sharing systems. From an information supply perspective, not all employees who come up with novel and valuable best practices are willing to share them (Neeley and Leonardi 2018), while other employees may overload the unstructured information

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<sup>1</sup> Results in prior studies are mixed. While some studies show that organizations fail to capitalize on the benefits of unstructured information sharing systems, other studies document a positive association between the use of ESNs and organizational learning (Huang, Singh, and Ghose 2015; Lam, Yeung, and Cheng 2016; and Aboelmaged 2018). However, the latter studies cannot conclusively support that the use of ESNs is the *cause* of the observed performance, as they rely primarily on surveys and/or archival data (where the archival data captures a time series of employee interactions in ESNs).

sharing system with low-value or even frivolous posts, just to be seen and heard (Oettl et al. 2018). From an information demand perspective, many employees who could benefit from learning about best practices find the search for them time-consuming and/or unproductive (Levine and Prietula 2012). This is because unstructured information sharing systems are often overloaded with information irrelevant to the needs of their users.

Scholars and practitioners increasingly recommend adding structure to unstructured information sharing systems to enhance *productive* knowledge sharing and learning (Oleson 2013; Charki, Boukef, and Harrison 2018). SSBP, the management control mechanism that involves high-performing units periodically sharing best practices in a structured manner, can potentially overcome the aforementioned information supply and demand problems. SSBP can motivate knowledge sharing by high-performers who might be encouraged by the formal recognition and legitimization of their distinctive practices and/or the opportunity to help others and be recognized.<sup>2</sup> More importantly, SSBP can serve as a decision-facilitating mechanism for employees demanding high-quality knowledge to make valuable and timely decisions (Demski and Feltham 1976) in an environment prone to information overload.

In sum, SSBP enables units to (a) more easily uncover valuable ideas by directing their attention to high-quality ideas, (b) trust those ideas, as they come from high performers,<sup>3</sup> (c) understand those ideas, as they have a clear structure that integrates actions and results, and (d) minimize the costs of searching for relevant knowledge in an unstructured information sharing system.

Companies can generally expect the benefits of SSBP to expand as the learning units get exposed

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<sup>2</sup> Research shows that altruism (the perception of being helpful to others) and recognition (being recognized by and receiving feedback from others) can motivate people to share information in social networks (Constant, Sproull and Kiesler 1996, Brzozowski, Sandholm and Hogg 2009).

<sup>3</sup> Studies show that employees are more likely to seek information on best practices from coworkers who they know are top performers (Song et. al 2018; Deller and Sandino 2020).

to an increasing number of best-practices ideas and experiment with implementing them over time, leading to a more positive performance trend.

SSBP, however, is not guaranteed to improve knowledge sharing and performance trends. It could have no effect or even backfire if (a) high-performing units do not know what actions led to their success and, consequently, have no useful best practices to offer; (b) internal competition and fear of giving away relative advantages keeps high-performing units from sharing their best ideas (Butt, Antia, Murtha, and Kashyap 2018; Li and Sandino 2018); (c) learning units do not find the shared practices applicable or do not have the time, ability, or resources to replicate them (O'Dell and Grayson 1998); (d) learning units fixate on the limited set of ideas featured in BP posts, ignoring other relevant ideas shared through the unstructured information sharing system; or (e) employees in non-BP units are dissuaded from sharing ideas because the more structured mechanism for knowledge sharing - SSBP - could diminish their intrinsic motivation to contribute to the unstructured information sharing system (Lam and Lambermont-Ford 2010).

Given the competing arguments on the direction of the average effect of SSBP, we state hypothesis 1 in the null form:

*Hypothesis 1: The structured sharing of best practices in an unstructured information sharing system will have no effect on a business unit's performance trend.*

To unpack the average effect of SSBP on performance trends, we test whether conditions affecting the benefits and costs of structured sharing on an unstructured platform moderate the performance effects on learning units.

## **2.2. Potential Moderators of the Effectiveness of Structured Sharing of Best Practices**

### ***2.2.1. Benefits from Reducing the Costs of Finding High-quality Information in an Unstructured Information Sharing System***

As explained in Figure 1, we conjecture that units will benefit more from SSBP when they are otherwise overloaded with online information and/or underexposed to best practices information, or when SSBP increases exposure to higher-quality, novel information.

#### ***a. Information Overload***

Research suggest that information helps employees improve their decisions and performance up to a point, beyond which information overload (or “too much information”) brings about a rapid decline in performance. Information overload adds noise to the decision-making process, creates confusion, makes it harder to recall relevant information, and adds psychological stress (Bawden and Robinson 2009; Eppler and Mengis 2004).

Overload typically occurs when the requirements to process information exceed the individual’s processing capacity (in terms of time and ability). Employees may find that overload makes information too hard to process to be useful, undermining the intended decision-facilitating role of an unstructured information sharing system.

We expect that SSBP will help employees who perceive an overload of information in an unstructured information sharing system by (a) reducing their need to process large amounts of data to find valuable information and (b) enhancing their ability to process the given information. Furthermore, prior studies show that increasing information quality can greatly reduce perceptions of information overload (Simpson and Prusak 1995). SSBP is designed to improve information quality and reduce perceived information overload as the information comes from verified high-

performing units, integrates actions and results into clearly organized best-practice knowledge, and is placed at predictable “locations” in the system. We therefore hypothesize:

*Hypothesis 2: Structured sharing of best practices in an unstructured information sharing system will lead to more positive effects on performance trends in units whose employees perceive higher information overload in the system than in units whose employees perceive lower information overload.*

***b. Lower Exposure to Knowledge due to a Lack of Connection to Peers***

Unstructured information sharing systems can be overwhelming for isolated users, but those with a network of trusted peers find them more manageable. Trusted peers can provide valuable guidance within the system: they can forward posts related to best practices and/or share their experiences and opinions on those practices.

Geographic distances affect connections to trusted peers both in the real world and in online social networks. Studies have found that geographical clusters stimulate networking among nearby units and increase the diffusion of knowledge (Baptista 2000; Bailey et al. 2018). Conversely, employees of units distant from other units have fewer opportunities to build social networks within the information system, resulting in lower knowledge acquisition (Singh, Hansen, and Podolny 2010). Without SSBP, employees from units located far from other same-company units may struggle to find relevant information in the unstructured information sharing system. SSBP could address this by highlighting the most useful information for these users, reducing their costs of finding relevant information. Thus, we hypothesize:

*Hypothesis 3: The structured sharing of best practices in an unstructured information sharing system will lead to more positive effects on performance trends in units located*

*further from other same-company units than in units located nearer to other same-company units.*

Nevertheless, it is still possible that units located closer to other units would benefit more from SSBP, for example, if the *content* of the best practices shared is not entirely self-explanatory and/or not applicable to the focal unit's *context* (Argote et al. 2022) and discussions with peers from nearby units could help employees better adapt best practice ideas in the system to their own context (Audretsch 1998).

***c. Lower Exposure to Knowledge Due to a Less-competent Manager***

Even in isolated units, employees could learn best practices from supervisors overseeing—and possibly learning from—multiple units under the same supervisor. These supervisors could earn supervisees' "competence trust" by demonstrating ability, experience, and expertise (Das and Teng 2001), rendering those supervisees more likely to rely on best practices highlighted by that supervisor and thus less likely to depend on learning from high-performing units once the SSBP is put in place. Indeed, Levine and Prietula (2012) find that the benefits of knowledge exchanges at a global consulting company were lower where the organization had alternative formal mechanisms (such as online training) to support learning. Such mechanisms substituted for (rather than complemented) peer-to-peer knowledge exchange. We argue that this could occur in our context and therefore hypothesize:

*Hypothesis 4: The structured sharing of best practices in an unstructured information sharing system will lead to more positive effects on performance trends in units whose managers are perceived to be less competent than in units whose managers are perceived to be more competent.*

Even so, it is possible that the structured sharing of best practices in an unstructured information sharing system may yield better results if competent managers could help adapt the outside ideas featured in SSBP to the local conditions and produce better results. Thus, whether employees' trust in management's competence increases or decreases the benefits of SSBP is an empirical question.

#### ***d. Higher-quality Best-Practices Information***

Search costs due to information overload can be attributed in part to variations in the overall quality or usefulness of the available information (Eppler and Mengis 2004). Assuming the benefits from SSBP are due to reducing search costs for high-quality information, we expect not only that SSBP will yield greater results when the cost of accessing best-practices information is reduced (as articulated in Hypotheses 2–4), but also when the quality of the shared information is higher—easy to understand and relevant for decision-making (Gorla et al. 2010). Expecting employees to view and react more frequently to posts containing higher-quality information, we hypothesize:

*Hypothesis 5: Ex post, the structured sharing of best practices in an unstructured information sharing system will lead to more positive effects on performance trends in units exposed to higher-quality best practices posts than in units exposed to lower-quality posts.*

Alternatively, if the effects of SSBP on performance are not related to access to high-quality best-practices information but rather to other factors, such as employees reacting to increased pressure or incentives to be recognized, then units' efforts and performance will respond similarly to higher- and lower-quality posts.

### **2.2.2. Costs from Fixating on a Narrower Set of Practices**

#### ***a. Differences in the Markets Served by the Best Practices Units and the Learning Units***

Unstructured information sharing systems often connect units serving different markets, exposing them to a broad range of ideas.<sup>4</sup> SSBP, however, is likely to impose a cost: directing attention to the ideas of a narrow set of BP units, potentially resulting in exposure to fewer ideas overall. Considering that an unstructured information sharing system may be overloaded with information, the SSBP will likely have a more positive effect on learning units serving markets more similar to the BP units' markets, as more of that shared knowledge will be applicable and actionable (Zhang et al. 2020). Indeed, Hansen (2002) and Levine and Prietula (2012) highlight that knowledge sharing only pays off if the practices shared by one unit can be reasonably useful to the learning units. However, for units serving markets different from the BP units' markets, exposure to the SSBP's narrower set of ideas may focus too much attention on ideas that are not applicable to them and too little on more-applicable ideas found elsewhere in the system. We therefore hypothesize:

*Hypothesis 6: The structured sharing of best practices in an unstructured information sharing system will lead to worse performance in units serving markets that diverge more from the markets served by the best practices units than in units serving markets that are more similar to the markets served by the best practices units.*

SSBP may nevertheless benefit units serving different markets than those served by the BP units if it directs their attention to novel and useful ideas they would not have considered otherwise.

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<sup>4</sup> This is a valuable feature of unstructured information sharing systems. The organizational knowledge creation theory indicates that more diverse ideas and experiences lead to greater innovation (Nonaka and Krough 2009). Accordingly, Li and Sandino (2018) found that introducing an information system to share creative work at a mobile phone retailer resulted in greater benefits for units operating in more divergent markets that required more customized and differentiated service. Exposed to a broader set of ideas, those units experienced increased creativity and employee engagement.



### ***b. Reduction in Voluntary Knowledge Sharing Outside the SSBP Mechanism***

Another potentially negative consequence of SSBP is that it may reduce the natural motivation non-BP unit employees have to share their own ideas and practices. Research suggests several factors that could motivate employees to share knowledge voluntarily in an unstructured information sharing system, including: (a) altruism (Constant, Sproull, and Kiesler 1996); (b) reciprocity (Constant et al. 1996); (c) feedback and recognition (Brzozowski, Sanholm, and Hogg 2009); and (d) self-promotion (Wasko and Farah 2005). SSBP could weaken such motives for non-BP units for three reasons. First, it could crowd out altruistic and reciprocity motives via a perceived decrease in responsibility and autonomy to share knowledge (Lam and Lambermont-Ford 2010). Second, it could reduce the potential for feedback and recognition if these latter benefits of sharing best practices shift to the BP-unit employees in the SSBP. Third, it could make individuals worry about judgment of their shared content compared to that of the BP units. We therefore hypothesize:

*H7: The structured sharing of best practices in an unstructured information sharing system will lead to lower sharing of information outside the structured mechanism for sharing best practices.*

It is possible, however, that SSBP could instead *increase* the posts contributed by non-BP-unit employees if it (a) models a constructive way to create and share information on best practices, (b) motivates employees to share ideas to gain visibility and have their own units become BP units, or (c) promotes discussion of ideas more relevant to the unit's work.

### III. RESEARCH SETTING AND INTERVENTION

#### 3.1. Research Setting

Our research setting is a large grocery store chain that implemented SSBP in one of the countries in which it operated. Each franchisee owned exactly one store and kept the residual profit of that store after paying a royalty to the company.<sup>5</sup> Franchisees made investment, purchasing, and hiring decisions and could generally run their stores as they saw fit. However, the retailer implemented structures that guided—and, to an extent, limited—franchisees’ actions.<sup>6</sup>

The company had implemented its ESN a few years before this study began. Any employee on this unstructured ESN could, at any time, form groups; create and share posts or photo/video albums; comment on posts; “like” or otherwise react to posts (e.g., with a “heart” or a “happy face” symbol); and/or send public or private messages to others. At the beginning of 2019, employee engagement with the ESN was high, with more than 85 percent employees active in the system. However, many users complained that the ESN was overloaded with information, making it difficult to find relevant content. From 2016 to 2019, there were on average close to 850 posts and 1,200 comments every month in the main regional and product category groups, two of the most accessed groups in the ESN. Appendix 1 shows randomly selected ESN posts from this time. In general, they were work-related, as the company had provided a guideline asking employees not to share content unrelated to work. However, information on best practices was often incomplete and scattered throughout the ESN, buried in a large volume of information. Most posts were

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<sup>5</sup> The company had a policy of granting only one store per franchisee (avoiding multi-unit franchising), because it wanted to encourage all franchisee-store managers to focus their entire attention on their store. The company enabled its best franchisees to switch to larger, more profitable stores when new stores became available.

<sup>6</sup> For example, the retailer required franchisees to maintain a consistent store layout of product categories but allowed them to determine the layout within each area. The retailer set an upper limit on product pricing but otherwise allowed franchisees to set their own prices. It also required franchisees to choose merchandise from a list of approved products but franchisees could seek authorization to introduce new products. Franchisees were encouraged to use digital systems developed by the head office for personnel and inventory management.

announcements (related to marketing, operations, or training) or congratulations (related to an employee's, a store's, or a region's good work or an employee's anniversary at work). Stores also posted requests to each other for supplies or inventory. Only a few posts (a) shared sales results, although without explaining how they had been achieved, or (b) recommended actions, although without verified results. None in this randomly selected sample of posts described both (a) recommended practices *and* (b) results linked to those practices.

To promote productive knowledge sharing and improve performance, the company pilot tested SSBP in 2019. In the country where we conducted our study, the retail company had over 600 stores in 12 regions, with an office overseeing each region. Before the study took place, one of those regional offices had already tried an initiative on the ESN promoting best practices among its stores. Further development of this initiative resulted in the SSBP intervention, which was then pilot tested in five other regions (while the remaining six regions continued their usual use of the ESN without SSBP). The company then implemented SSBP across these regions.

The HR team (in charge of the ESN) set up this SSBP as a natural field experiment, which had significant advantages for research. We were able to draw causal inferences, thanks to the random selection of the treatment stores, and to examine the effects of SSBP in a natural context (Bandiera et al. 2011, Floyd and List 2016). Subjects were unaware that they were participating in a study, helping us discard self-selection or a “Hawthorne effect” as alternative explanations for our results. The company shared all the resulting data with our research team to facilitate our analysis of the effects of SSBP.

### **3.2. Randomization**

Treatment regions were selected with a stratified randomization strategy. The 11 regions used to test SSBP were split into three strata based on store-level weekly sales trends over the 12 months

before the intervention, and regions were randomly assigned to treatment and control groups within each stratum: low sales trends (2 regions: 1 treated, 1 control), medium sales trends (5 regions: 2 treated, 3 control), and high sales trends (4 regions: 2 treated, 2 control). The randomization strategy required us to bundle the two regions with the highest risk of “contamination” (Regions 2 and 8) into the same (treatment) group, as employees from these regions regularly interacted. Allocation of regions and stores into treatment and control groups is shown in Panel A of Table 1.

To uncover the potential benefits of SSBP, the company focused its intervention on five product categories: fresh goods (23.3% of sales), dry goods (19.5% of sales), beverages (11.9% of sales), fruits and vegetables (11.5% of sales), and bread (4.7% of sales). These categories were chosen to account for most sales while minimizing SSBP implementation costs.<sup>7</sup> They had reasonable variation in sales across stores and their sales level depended on the store teams’ efforts. Prior to the intervention, we conducted power analyses with simulated sales data from the previous 12 months<sup>8</sup>.

To make sure that the randomization strategy worked well and generated comparable control and treatment groups, we collected data on pre-intervention characteristics of each store and its municipality (for example, demographics of the customer base in that area) and compared these characteristics between the treatment and control groups (see Panel B of Table 1). Store age and

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<sup>7</sup> As we will describe later, information about best practices was collected and organized by the regional office for each selected category; thus, the more categories covered, the greater the effort and cost.

<sup>8</sup> These analyses aimed to verify that our planned tests would identify any meaningful effect of SSBP on sales; they assumed a significance of 10 percent ( $\alpha=0.1$ ; two-sided tests) and showed that we could be 80-percent confident that we would identify effects of SSBP equal to or greater than a 1.3-percent change in sales. The managerial team considered these minimal effect sizes “reasonable,” given the effects of past sales initiatives. In our power analyses and subsequent formal analyses, we removed weeks that, according to the company, were historically associated with extremely volatile sales (such as holidays and vacations), as these would add significant noise to the estimation and reduce the ex-ante power of the tests.

pre-existing sales level were the only two characteristics showing a statistically significant difference between the treatment and control groups: treatment stores tended to be younger and have lower levels of sales (although not lower sales trends). These differences were controlled for in our regression analyses estimating the treatment effects.

### **3.3. Details of the Intervention**

From August 26 to December 31, 2019, the five treatment regions featured and pinned best practices posts (or BP posts) from their high-performing stores on their corresponding regional group on the ESN. According to the HR managers, these posts remained on the albums of the ESN in those regions after December 31, 2020. None of this was done in the six control regions. Figure 2 shows the intervention timeline.

The corporate HR team and the managers in each treatment region collaborated to select eight high-performing stores from each region, to be featured from August to November 2019. Selection was based on proprietary information (including profitability measures and other soft information) that was inaccessible to us.<sup>9</sup> Every month, two of each region's selected stores would be featured in a BP post two weeks apart. Each post was pinned to the top of its corresponding regional group on the ESN for the two weeks it was featured, until the next BP post replaced it. All BP posts were kept in the group's archive (accessible to all store teams in the region) once unpinned.

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<sup>9</sup> Untabulated analyses show that the likelihood of a store being selected in a treated region was significantly correlated ( $p \leq 0.01$ ) with the performance measure that we used in our study (*log sales*) as measured in the pre-intervention period. Regarding the implementation of SSBP, 36 of the 40 pre-selected stores followed the intervention schedule to make BP posts, but four (from three regions) did not make BP posts by the end of the intervention period (December 31, 2019). The reasons provided were that they had conflicts with preparations for the holiday season and (in two cases) that the main best practices the managers planned to share had already been covered. This indirectly shows that sharing best practices was voluntary in this setting. Neither regional managers nor the regional sales managers could force or pressure the stores to share.

To identify the effect of SSBP from the idiosyncrasies of each treatment region’s sharing practices and to ensure the quality of the SSBP intervention, sales managers from each treatment region had to follow a protocol ensuring that SSBP was implemented consistently across the regions. Each month, sales managers from the region visited the selected high-performing best-practices stores (hereafter, BP stores), recorded the best practices highlighted by the store manager in the five featured product categories, and did a “walk-through” of the store with the store manager to take photos and videos of those best practices. Afterwards, these regional sales managers composed the BP post for the regional group—with texts, photos, and/or videos—in the form of an album, with the same structure across all treatment regions (see Figure 3). The regional sales managers’ role was limited to recording the best practices and visual content highlighted by the store manager, following the predetermined structure for the SSBP posts (rather than selecting the practices or content of the posts). Employees from the region could easily identify the main post as being about best practices from a high-performing store in the region. They could also see information about the store and its owner, a link to the album, and an overview of its photos and videos. Once they clicked on a photo, they could see a visual representation of the best practice (for example, how best to display bananas). The post made it clear that the content was shared by the featured high-performing store (even though it was uploaded in the system by a regional sales manager).

Appendix 2 presents representative SSBP posts. The vast majority presented an appealing picture of a product/aisle display with an explanation of why the store staff designed it that way and the results obtained. Store managers sometimes emphasized the relevance of empowering employees to make sure they took ownership of product decisions; for example, by accounting for local preferences, addressing product-related challenges (e.g., not mixing up goods with different expiration dates), and improving product handling. We observed a few conflicting posts. For

instance, while the fruits-and-vegetables post in Appendix 2 (post 5, from an urban store) recommended positioning bestselling products at all counters to “bring up the volume and growth of bestsellers,” a fruits-and-vegetables post from a store in a less-populated area recommended placing bestseller products on “less” attractive spaces, since customers would seek them out wherever they were placed. This suggested that stores had different perspectives on what constituted best practices, potentially reflecting local customer preferences.

The BP posts received a fair amount of attention. Within each treated region, we tracked the “likes” and comments for each BP post and the number of users who had seen them. On average, within two weeks of posting, an SSBP post received 33.5 “likes” (up to as many as 100) and nearly three comments (up to as many as 22) and was seen by 489 users (up to as many as 830).

### **3.4. Pre- and Post-intervention Surveys**

The company implemented a pre- and a post-intervention survey to collect more data about the employees’ experience at work and use of the ESN, such as their perceived level of information overload in the ESN and their trust in the regional manager’s competence.

Employees from 491 stores in the 11 regions we analyzed responded to the pre-intervention survey.<sup>10</sup> Eighty-five percent of those responses indicated that they had used the ESN system for more than five minutes a week over the past two months.

The pre-intervention survey suggested that employees appreciated information gathered from the ESN. Using a Likert scale in which 1 = never, 2 = rarely, 3 = sometimes, 4 = very often, and 5 = always, employees replied, on average, with “very often” to the statement “The information on [the ESN] helps me do my job better” (mean=3.8, median=4). For employees applying ideas found

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<sup>10</sup> These 491 store-level responses were entered by one or two individuals per store. We averaged out responses where more than one individual entered a response for a store.

on the ESN, the top three characteristics of the ideas they adopted were that they were (a) creative or novel (36% of responses); (b) posted by individuals who had already generated positive results (29% of responses); and (c) easy to copy (13% of responses).<sup>11</sup>

Despite such evidence of using the ESN to share knowledge, we also confirmed the concerns that led management to implement SSBP. Using the same Likert scale, respondents replied, on average, with “sometimes” to “very often” to the statement “I am *overwhelmed* by the amount of information on [the ESN]” (mean=3.5); we used the response to this question as a measure of information overload. Furthermore, consistent with arguments leading to Hypothesis 2, untabulated correlation analysis of pre-intervention survey responses suggested that employees experiencing information overload in the ESN were less likely to find useful information there.

## IV. EMPIRICAL ANALYSES AND RESULTS

### 4.1. Final Sample for Data Analyses and Descriptive Statistics

The SSBP intervention was launched in late August 2019 and lasted until the end of December 2019. In our analyses, we define August 1, 2018 to the start of the intervention in August 2019 as the pre-intervention period (Post=0) and the last week of August to the end of January as the intervention period (Post=1). In line with the *ex ante* study design (including stratified randomization and pre-intervention power analyses), we used a 12-month pre-intervention

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<sup>11</sup> The following question was asked:

The ideas from the ESN system during the last two months that I have applied are because . . .

(please select up to three reasons)

\_\_\_ they are creative or novel.

\_\_\_ they are easy to copy.

\_\_\_ they have been shared by top-performing stores.

\_\_\_ they have been shared by people I trust.

\_\_\_ they have many “likes.”

\_\_\_ the ones who shared the idea have shown they have already generated positive results.



period—seven months longer than the post-intervention period—in our analyses to better capture both the sales trend leading up to the intervention and the seasonality in the data.<sup>12, 13</sup>

Our final dataset has 31,759 store-week observations (containing the sales of the five product categories featured in BP posts). Panel A of Table 2 shows summary statistics of our sample data. Our main dependent variable is the natural log of sales (as the intervention was designed to increase sales). Sales—reported in US dollars rather than the local currency to protect company confidentiality—vary widely across store-weeks. An average store sells US\$ 98,020 of groceries each week, though weekly sales range from US\$ 1,062 to US\$ 319,316.<sup>14</sup> Observations from the treatment group account for 46 percent of the store-week observations.

To test Hypotheses 2–6, we constructed five moderating variables: *Information Overload*, *# of Nearby Stores*, *Trust in Regional Manager Competence*, *Post Quality*, and *Divergence from BP Stores*. Later, we turn each moderator into (a) a dummy indicating whether or not the underlying raw measure was above the sample median and (b) a normalized z-score version of the measure (subtracting the mean from each raw measure and dividing it by its standard deviation). We do not include these transformed measures in Table 2 but use them in our regression analyses for ease of interpretation (Tables 5–9).

We expected that the benefits of SSBP would be greater when the costs of searching information were higher, that is, under conditions of heightened information overload or reduced guidance

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<sup>12</sup> We conducted untabulated robustness checks including only 5 months of the pre-intervention period in the final data analysis. Our results remain similar. In fact, the positive effect on sales trends becomes stronger if we include only the previous 5—rather than 12—months as the pre-intervention period. We keep the 12-month pre-intervention period to be consistent with the *ex ante* study design that generated the randomization outcomes.

<sup>13</sup> The Covid-19 pandemic (which hit the area in which our research sites are in late February 2020) limited the number of post-intervention months that can be reliably included in the data analyses and our ability to observe the long-term effect of the intervention. In an untabulated robustness test, we include February 2020 as a post-intervention month and our results remain similar.

<sup>14</sup> We dropped store-weeks in which the store was closed for remodeling or renovation for at least part of the week and hence had extremely low sales (typically below US\$ 110). Results are robust to including these outlier values.

from a network of peers or competent regional managers. *Information Overload* is measured as the average value of the responses provided by each region's store employees to a pre-intervention survey question asking about the extent to which the statement "I am overwhelmed by the amount of information on [the ESN]" described their experience using the ESN system. On a scale from 1 (never) to 5 (always), the average value for *Information Overload* is 3.5; it ranges from 3.2 to 4.0. *# of Nearby Stores*, the number of same-company stores within 10 kilometers of the focal store, measures prior exposure to a network of peers from same-company stores. The average number in our sample is close to 17; it ranges from 0 to 78. *Trust in Regional Manager Competence* is measured using the principal component from three pre-intervention survey questions related to the regional manager. Respondents were asked to indicate, on a Likert scale from 1 (never) to 5 (always) (including a "Not Applicable" option if they did not know the regional manager), the extent to which each of the following statements described their experience at work: (1) "The regional manager is very capable of performing her/his job"; (2) "The regional manager is known to be successful at the things he/she wants to implement"; and (3) "I feel confident about the regional manager's skills." The principal component explains 88.8 percent of the variation in the three questions. The loadings of Questions 1–3 into the principal component measure are 0.580, 0.572, and 0.581, respectively. This measure also varies widely, from -1.193 to 0.925.

Our expectation was that implementing SSBP would also improve results by increasing the quality of the posts. To evaluate this, we measure *Post Quality* as the average number of reactions ("likes," "hearts," and so on) to the BP posts within two weeks of posting which ranges from 22.5 to 65 (with a mean of 35.8).

Conversely, we expected that SSBP might hinder performance if it narrowed attention to a few posts and diverted attention from more relevant ones, especially for stores that differed

significantly from the BP stores in the SSBP. *Divergence from BP Stores*—the average number of kilometers between the focal store and the BP stores in its region—measures the difference in market characteristics between the learning store and the BP stores, as stores farther from each other are more likely to have different markets. The average value is close to 38 kilometers.

In Panel B of Table 2, univariate correlations show that sales on average were lower in the post-intervention period, possibly due to cyclicity. Stores in the SSBP treatment group had lower sales than those in the control group, which is consistent with the fact that treatment stores had lower sales levels in the pre-intervention period as seen in Panel B of Table 1. However, we note that differences in sales *levels* between treatment and control stores did not translate into pre-existing differences in sales *trends* as sales trends were the basis for randomization. We also observe that sales are positively and significantly correlated with # of nearby stores (exposure to a network of peer stores), post quality, and trust in regional manager’s competence (greater reliance on managers for BP knowledge), but negatively and significantly correlated with perceived information overload. Being in the treatment group (SSBP) is positively and significantly correlated with the number and percentage of posts a store shared in the regional group. Next, we introduce a model to fully capture the dynamics of sales changes over time and across the treatment conditions and to estimate the effects of the SSBP intervention.

#### **4.2. Effects of Structured Sharing of Best Practices**

First, we visualize the treatment effect of SSBP on financial performance by plotting the adjusted natural log of weekly sales ( $\ln(\text{Sales})$ ) against time, contrasting the treatment and control groups. In Figure 4, the vertical axis is the residual of regressing  $\ln(\text{Sales})$  on store fixed effects, week

fixed effects, and store-time-trend fixed effects.<sup>15</sup> The horizontal axis represents time (in weeks). Prior to the SSBP intervention, the treatment and control groups exhibited similar sales trends, as we had ensured during randomization. Following SSBP, the sales trends for the treatment and control groups gradually diverge, with the treatment group showing a relatively favorable sales trend over time. This is consistent with our expectations that the learning effect of knowledge sharing associated with SSBP is best captured by a sales-trend effect (rather than an average treatment effect on sales level).

We examine changes in the sales performance improvement of the treated stores relative to that of the control stores. Specifically, we estimate the following model:

$$\begin{aligned} Ln(Sales)_{it} = & \delta_0 + \delta_1 Post_t + \delta_2 SSBP_i \times Post_t + \delta_3 Time_t \\ & + \delta_4 Time_t \times Post_t + \delta_5 SSBP_i \times Post_t \times Time_t + \delta_L \text{ Store Fixed Effects} \\ & + \delta_M \text{ Week Fixed Effects} + \delta_N \text{ Store Trend Fixed Effects} + \varepsilon_{it}, \end{aligned}$$

where  $Ln(Sales)_{it}$  is the natural log of sales for store  $i$  in week  $t$ ;  $Post_t = 1$  if week  $t$  is or comes after the first week of SSBP;  $Time_t$  is the number of weeks relative to the first week of the initiative (-52 to +22, with 0 being the first week);<sup>16</sup> and  $SSBP_i = 1$  if store  $i$  is a treatment store. The main focus of our estimation is the *sales-trend effect* ( $\delta_5$ ); that is, the change in sales relative to that of control stores for each passing week since the beginning of SSBP. Therefore,  $\delta_2 + Time_t * \delta_5$  will be the total *Sales Effect as of Time t*; that is, the change in sales relative to that of control stores by

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<sup>15</sup> Like Deller and Sandino (2020), we assess the effect of the system intervention (SSBP) on the natural logarithm of sales because (a) we aim to analyze the effect of SSBP on the percentage change in sales, given that the initial level differed across stores, and (b) the natural logarithm of sales was closer to being normally distributed, in line with the assumptions necessary to run OLS regressions.

<sup>16</sup> The last round of BP posts was put into the ESN in December 2019 (18 weeks after the start of the initiative). We included four additional weeks of sales data (until the end of January 2020) in our analyses because it would take time for people to learn from and apply the ideas from these final BP posts.

the end of week  $t$ . Standard errors are clustered by region.<sup>17</sup> Notice that the 36 BP stores are also likely to benefit from the intervention in the periods when they are not themselves the source of ideas. Nevertheless, we conduct robustness tests that replicate all of our analyses excluding these 36 stores from the sample.

We test Hypothesis 1 by estimating the above model in our full sample and examine the effect of SSBP on sales and on the sales trend.<sup>18</sup> In Table 3, the interaction term between *SSBP* and *Post* has a statistically insignificant coefficient, indicating that the intervention had little effect on sales at first (week 0). However,  $\delta_5$  (the coefficient for  $SSBP \times Post \times Time$ ) is positive and significant at the 5% level, indicating that SSBP had a positive and significant effect on sales with each passing week. If we multiply this coefficient by 18 and take the exponential, we can see that the sales-trend effect of the 18-week intervention resulted in the treatment group's sales being 3.67 percent ( $e^{(0.002*18)} - 1$ ) higher than those of the control group.<sup>19</sup> Our results show that, consistent

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<sup>17</sup> Our empirical model corresponds to a multigroup interrupted time-series model (Kontopantelis et al. 2015, Linden 2015), as it examines treatment effects on time trends. Specifically, the formula on page 483 of Linden (2015) is exactly our specification (except that the coefficients  $\beta_4$  and  $\beta_5$  in their formula are absorbed by the store and store-trend fixed effects that we add). Given that store-trend fixed effects are included, we do not report the coefficient on *Time* because this coefficient, in our model, only represents the baseline sales trend for *one* of our sample stores (the algorithm selected this store) as the basis for reporting the sales trends for all other stores (hundreds of store-level time trends were estimated by the model, each corresponding to a unique store in the sample, but could not be reported due to space constraints). However, any interaction term between *Time* and *Post* captures the average effect across all stores (because we do not include separate interaction terms for each store). In sum, we control for all individual stores' time trends (accounting for differences in time trends across stores due to their age or other unobservable factors) while estimating the average effect of the intervention on the store sales trends ( $SSBP \times Post \times Time$ ).

<sup>18</sup> As this is a study with clustered randomization (at the regional level) and finer-level outcomes (at the store level), we (a) use store fixed effects (which subsume the region fixed effects) to account for regional level differences and (b) cluster the standard error by region (correcting for intra-cluster correlation that tends to overestimate statistical significance).

<sup>19</sup> The intervention's total effect ( $e^{(-0.00614+0.002*18)} - 1$ ), including the immediate effect and the learning effect, indicates that the treatment group's sales were 3.04 percent higher relative to the control group by the end of the treatment period.

with Hypothesis 1, SSBP improved the financial performance trend.<sup>20,21</sup> The effect took some time to manifest, consistent with the nature of SSBP and the learning outcome being a performance trend: it takes time for store managers and employees to read and understand the new posts every two weeks, discuss them, decide which best practices to implement, implement them, and wait to see if they work. SSBP’s significant effect on stores’ sales trends are robust to excluding the 36 BP stores, as are all subsequent results reported below.

If the main driver for improved performance had been due to the store employees’ motivation to gain recognition as a future BP store rather than due to the passing of useful knowledge, we would have observed an increase in efforts across all product categories and not just those featured in the BP posts (because the stores did not know what product categories would be featured). In untabulated results, we use the same model and test whether the intervention had a similar effect on a different sample including product categories *not featured* in the BP posts. We find that SSBP had neither an immediate effect on sales nor a “sales trend” effect (i.e., neither  $\delta_2$  nor  $\delta_5$  were significant) for those categories, suggesting that the improvement in sales performance is unlikely to be driven mainly by the desire to gain recognition as a high-performing unit.

To make sure that the observed effect was driven by the SSBP, rather than by concurrent confounding factors of which we were unaware—we also examine whether the positive treatment

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<sup>20</sup> The three-way interaction in our baseline model is similar to the two-way interaction in a standard difference-in-differences (DID) model: this key coefficient (on *SSBP x Post x Time*) shows how the time trend significantly changed in the post-intervention period for the treated stores. As an alternative specification, we constructed two post-intervention periods (i.e., dividing the post-intervention period into the first 9 weeks and the second 9 weeks) and ran a standard DID analysis (to show the change in the average sales *level*). In our untabulated analyses, we find that the intervention did have a positive and significant average effect on the sales level in the *second* post-intervention period, consistent with the treatment effects on sales becoming more positive and significant over time. The cutoff line for the two post-intervention periods, however, can be somewhat arbitrary. Even the split of the post-intervention period into two rather than three shorter periods can be arbitrary. Therefore, we keep the interrupted time-series analysis (focusing on sales trend) as our main specification.

<sup>21</sup> In untabulated analyses restricting the sample to stores without franchisee turnover we found that our results on the treatment effect (Hypothesis 1) still hold.

effect is stronger for the stores that reacted more to the BP posts. Specifically, in Table 4, we reran the baseline regression in the two subsamples resulting from splitting the stores based how many times a store reacted to the BP posts (e.g., with “likes”). In both subsamples, we see positive and statistically significant effects on sales trend. Interestingly, in the subsample with more store reactions (Column 2), the coefficient on  $SSBP \times Post$  is positive and significant, indicating an *immediate* effect of the intervention, suggesting either that some of the best practice ideas could be emulated and implemented in the week when they were shared, or that part of the employees’ reaction to the BP posts was to increase their effort. Furthermore, that positive effect of the triple interaction in the subsample with more reactions to the posts in column 2 is 5.7 times larger than in the subsample with fewer reactions to the posts in column 1. After 18 weeks, SSBP was associated with a sales-trend effect explaining 28.97-percent-higher sales in the treatment group relative to the control group.

In Columns 3 and 4, we combined the subsamples and examined the coefficient on the four-way interaction term ( $SSBP \times Post \times Moderator \times Time$ ), where *Moderator* was either (a) a dummy indicating that *store-level reactions* to the BP posts was above median (Column 3) or (b) the number of *store-level reactions* to the BP posts (Column 4). The coefficient on the sales trend is positive for both, but—consistent with the earlier subsample comparison—there was a more positive effect on the sales trend for the stores with greater reactions to BP posts. This gives us confidence that it was exposure to these posts that drove the effect on sales improvement.<sup>22</sup>

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<sup>22</sup> In untabulated analyses, we also use store prior performance as a moderator and find that stores with lower prior performance experienced greater improvement in sales trends. This, indirectly, shows that the practices shared by the selected high-performing units were indeed valuable and that these shared practices, rather than other factors, drove the observed treatment effect on sales trends.

### 4.3. Factors Moderating the Effectiveness of Structured Sharing of Best Practices

Next, we delve deeper into circumstances potentially moderating the effects of the intervention.

#### *Perceived Information Overload*

To test Hypothesis 2, we use perceived information overload as the moderator. In Table 5, the first two columns show the regression results for the two subsamples resulting from splitting the stores based on their value for perceived information overload prior to the intervention. In the subsample with lower *ex ante* perceived information overload (Column 1), the effect of SSBP on the sales trend was insignificant, while in the subsample with greater *ex ante* perceived information overload (Column 2), the effect was positive and significant. Consistent with Hypothesis 2, the ( $SSBP \times Post \times Moderator \times Time$ ) coefficients in Columns 3 and 4 are positive and statistically significant, suggesting a more positive effect on the sales trend when store employees perceived a higher level of information overload in the ESN prior to the intervention.<sup>23</sup>

#### *Exposure to Knowledge from Peer Stores*

To test Hypothesis 3, we use *# of Nearby Stores* as the moderator. Prior to SSBP, employees in stores with fewer nearby same-company stores were less likely to have a network of peers that would help them identify scattered best practices in the ESN and were therefore likely to find SSBP more useful. In Table 6, the first two columns show the regression results for the two subsamples resulting from splitting the stores based on the number of nearby same-company stores (measured by number of stores within a 10-kilometer radius of the focal store) in their region. In the subsample with fewer nearby stores, SSBP had a positive and statistically significant effect on the sales trend (0.00301; that is, after 18 weeks, SSBP was associated with a sales-trend effect

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<sup>23</sup> In all moderator analyses, the main effect on the moderator is not included in the regressions because the moderators are all store-level or region-level characteristics and their effects are subsumed by store fixed effects. This also explains why the adjusted R-squares do not change much once we add interactions with the moderators.



explaining 4.42-percent-higher sales in the treatment group relative to the control group). In contrast, SSBP seemed to have no impact on sales in the subsample with more nearby stores. In Columns 3 and 4, we combined the subsamples and examined the coefficient on the four-way interaction term ( $SSBP \times Post \times Moderator \times Time$ ). The coefficient is negative and statistically significant in both cases, consistent with the earlier subsample comparison; that is, there was a significantly less-positive effect on the sales trend (less-positive learning effect) for the stores with greater help to identify best-practice knowledge from a network of nearby peers prior to SSBP.<sup>24</sup> The results in Table 6 are consistent with Hypothesis 3: learning units with fewer nearby same-company stores prior to the intervention experienced greater sales improvement.

### ***Trust in Regional Manager Competence***

To test Hypothesis 4, we use *Trust in Regional Manager Competence* as the moderator. In Table 7, the first two columns show the regression results in the two subsamples with lower versus higher employee trust in the regional manager's competence prior to SSBP. For the lower-trust subsample, SSBP had a positive and statistically significant effect on the sales trend (0.0036; that is, after 18 weeks, SSBP resulted in 4.33-percent-higher sales in the treatment group than in the control group), while, for the high-trust subsample, the effect was insignificant. In Columns 3 and 4, we combine the subsamples and examine the coefficient on the four-way interaction term ( $SSBP \times Post \times Moderator \times Time$ ). The coefficient is negative in both cases (although statistically significant only in Column 3), consistent with the earlier subsample comparison.

The results in Table 7 are consistent with Hypothesis 4: units whose employees had *lower* trust in the regional manager's competence had greater improvements in sales, suggesting that SSBP could substitute for trust in management competence as a mechanism driving learning and unit

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<sup>24</sup> Results are similar when we define "nearby stores" as stores within 5 or 3 kilometers.

performance improvement over time. This is consistent with Levine and Prietula's (2012) suggestion that knowledge transfers among co-workers are less beneficial in organizations already providing greater learning support.

### ***Quality of BP Posts***

To test Hypothesis 5, Table 8 examines whether the quality of BP posts moderates the performance trend effects of SSBP. We use the popularity of the BP posts to measure their quality (*Post Quality*).

In Columns 1 and 2 of Table 8, we ran our baseline regressions in the two subsamples in which stores were exposed to relatively lower-quality (less-popular) BP posts and higher-quality (more-popular) BP posts. We find that the higher-quality-posts subsample experienced a positive and significant sales trend effect (the coefficient on  $SSBP \times Post \times Time$  is 0.0038 and is significant at the 1% level; that is, by the end of the 18-week intervention, learning from the BP posts resulted in 6.02-percent-higher sales in these stores than in the control group) while there was no effect for the lower-quality-posts subsample. In Column 3, we combine the subsamples and interact the binary indicator for being exposed to higher-quality posts with the sales-trend effect term ( $SSBP \times Post \times Time$ ), finding that the difference in the sales-trend effect between the subsamples is statistically significant.<sup>25</sup> In Column 4, we use the underlying raw measure for post quality as a continuous-value moderator and find a positive and significant interaction coefficient between the moderator and the sales-trend effect term ( $SSBP \times Post \times Time$ ), indicating that the sales-trend

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<sup>25</sup> Notice that in this particular table, the numbers of observations in the subsamples in the first two columns do not add up to the total observations in the three right-most columns. This is because the moderator measures (*Post Quality\_High* and *Post Quality*), having been constructed in relation to the BP stores, could only be obtained for the treatment stores. We therefore included *all* observations corresponding to the control stores in the subsamples in the first two columns.

effect of SSBP becomes stronger as the quality of BP posts increases.<sup>26</sup> This is consistent with access to higher quality posts as a mechanism driving the positive effect of SSBP on sales trends.

### ***Market Divergence***

To test Hypothesis 6, we use distance to the BP stores to measure the degree to which the markets served by the BP stores diverge from those served by the focal store—greater distance presumably making the information shared less relevant to the focal store. In Table 9, the first two columns show the regression results in the two subsamples that showed relatively lower and greater divergence from the BP stores in their region.<sup>27</sup> The intervention had positive and significant effects on the sales trend in both subsamples. But the effect is larger in magnitude in the subsample with lower market divergence from the BP stores. The magnitude of the coefficient (0.0029) for the low-divergence subsample (Column 1) suggested that, by the end of the 18-week intervention, the SSBP sales-trend effect resulted in 5.20-percent-higher sales in the treatment group relative to the control group. This is a much larger effect than the 1.10-percent-higher sales effect for the subsample with greater divergence from the BP stores (Column 2). In Columns 3 and 4, the coefficients on the four-way interaction terms are negative and statistically significant in both cases, consistent with the earlier subsample comparison. These results are consistent with Hypothesis 6. Although learning units serving different markets than the BP units could have found

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<sup>26</sup> We replicated the analyses in Table 8 using the number of comments made to the BP posts in the first two weeks after the posts were entered in the ESN. We do not tabulate these analyses, as the average number of comments per post was only three. Nevertheless, our results are consistent with those reported in Table 8: our sales-trend effect is driven by posts receiving more comments.

<sup>27</sup> In Table 9, as in Table 8, the numbers of observations in the subsamples in the first two columns do not add up to the total observations in the two right-most columns because the moderator measures (*Divergence from BP Stores* and *Divergence from BP Stores\_High*) could only be constructed in relation to the BP stores.

the shared best practices more novel, in fact they experienced smaller sales growth following the SSBP intervention as the BP posts were less likely to be applicable to them.<sup>28</sup>

We note that a focal store very near the BP stores could have learned their practices even before SSBP, resulting in less potential to benefit from the initiative itself. In untabulated analyses, we reran our analyses in Columns 3 and 4 of Table 9 excluding any stores within 10 kilometers of the BP stores. As expected, the exclusion resulted in an even stronger effect of *market divergence* on the magnitude of the sales-trend effect associated with SSBP.

### ***Effects of SSBP on Voluntary Inter-store Knowledge Sharing***

To test Hypothesis 7, Table 10 examines whether the BP posts changed individual stores' sharing behaviors and resulted in less voluntary inter-store information sharing on the ESN. We present results from difference-in-differences regressions finding that, contrary to expectations, the SSBP initiative increased the number of posts shared by store employees in the ESN regional groups (Column 1). Our results suggest an increase of 0.92-percent in the percentage of posts made in regional groups relative to the total posts made by employees in store and regional groups, in a given store-week.<sup>29</sup>

The increase in ESN posts by store employees in the regional groups (above and beyond BP posts entered by regional sales representatives) suggests that, rather than discouraging employees from

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<sup>28</sup> As a robustness check, we use an alternative measure of *Market Divergence* between the markets served by the focal store and the BP stores; namely, an aggregate measure of the differences between the demographic characteristics of the municipalities of the focal store and the average demographic characteristics of the municipalities of the BP stores in the same region. We consider five dimensions (population density, average age, household size, per-capita income, and education level) and use the methodology in Campbell, Datar, and Sandino (2009) to estimate the divergence measure as a sum of the normalized differences in the values of these dimensions between the focal store and the BP stores. The results are similar: SSBP was associated with smaller sales-trends when the markets served by the learning units and the BP units differed more from each other (greater *Market Divergence*).

<sup>29</sup> As changes in ESN posts can be immediate outcomes of the SSBP intervention and be less subject to gradual trends, we use standard difference-in-differences analyses to estimate the average effect of the intervention on ESN posts.

sharing content with other stores on the ESN, SSBP triggered more of it. We find no significant decrease in the number or percentage of posts shared by employees in any treated region.

## V. CONCLUSION

We use data from a natural field experiment in a large retail chain to examine the effects of structured sharing of best practices in an existing unstructured information sharing system. Consistent with our hypothesis, our results show an improvement in sales trends in the treatment group relative to the control group—a 3.67-percent sales increase by the end of the 18-week intervention. This effect was stronger for stores that reacted more to the BP posts. Furthermore, consistent with the benefits of SSBP, the effect was more positive in stores (a) whose employees perceived more information overload using the ESN prior to the intervention, (b) with *less* guidance to uncover best practices (due to lower exposure to a network of peers or a competent regional manager), and (c) that were exposed to higher-quality posts. Consistent with the costs of SSBP, the intervention was found to be less beneficial in stores serving markets that differed more from the markets served by the BP stores. Overall, these results suggest that SSBP can improve sales, but that such results depend on a given unit’s condition. We find evidence that SSBP had a positive spillover effect, increasing (rather than decreasing) voluntary inter-store knowledge sharing outside the structured sharing mechanism.

While our results are robust to alternative specifications, they should nevertheless be interpreted with caution. First, because the company implemented the intervention following the protocol of a natural field experiment, it confronted limitations that could have reduced the power of the tests. For example, to ensure consistent treatment quality, regions or stores were not free to customize the content or format. Second, although the BP posts could not be directly shared outside of the regional group in the ESN, and the company took care to minimize risks of “contamination” by

assigning regions that were likely to communicate with each other (outside of the ESN) into the same treatment or control group, we could not completely track if contents from the SSBP were saved by employees in the treatment group and shared with someone in the control group. In that case, the effect of the intervention could have been under-estimated. Third, certain features of the field site may limit the generalizability of our findings. For example, unit (store) managers in our setting were franchisees who had no pressure to participate in the intervention but had strong incentives to create value from useful information shared in the ESN. However, our findings could generalize to any interventions consisting of structuring and sharing information from high-performing units within an *existing* ESN or similarly unstructured information sharing system, provided employees are motivated to perform. Fourth, although system records from the ESN show that stores continue to access and react to the BP posts shared during the intervention (even “new” stores that were opened after the intervention accessed the posts), the long-term learning effects of SSBP (beyond the 18-week period we analyzed) remain unclear due to the duration of the designed intervention and the limited data availability after the onset of the COVID-19 pandemic. Future research can explore effects of longer interventions.

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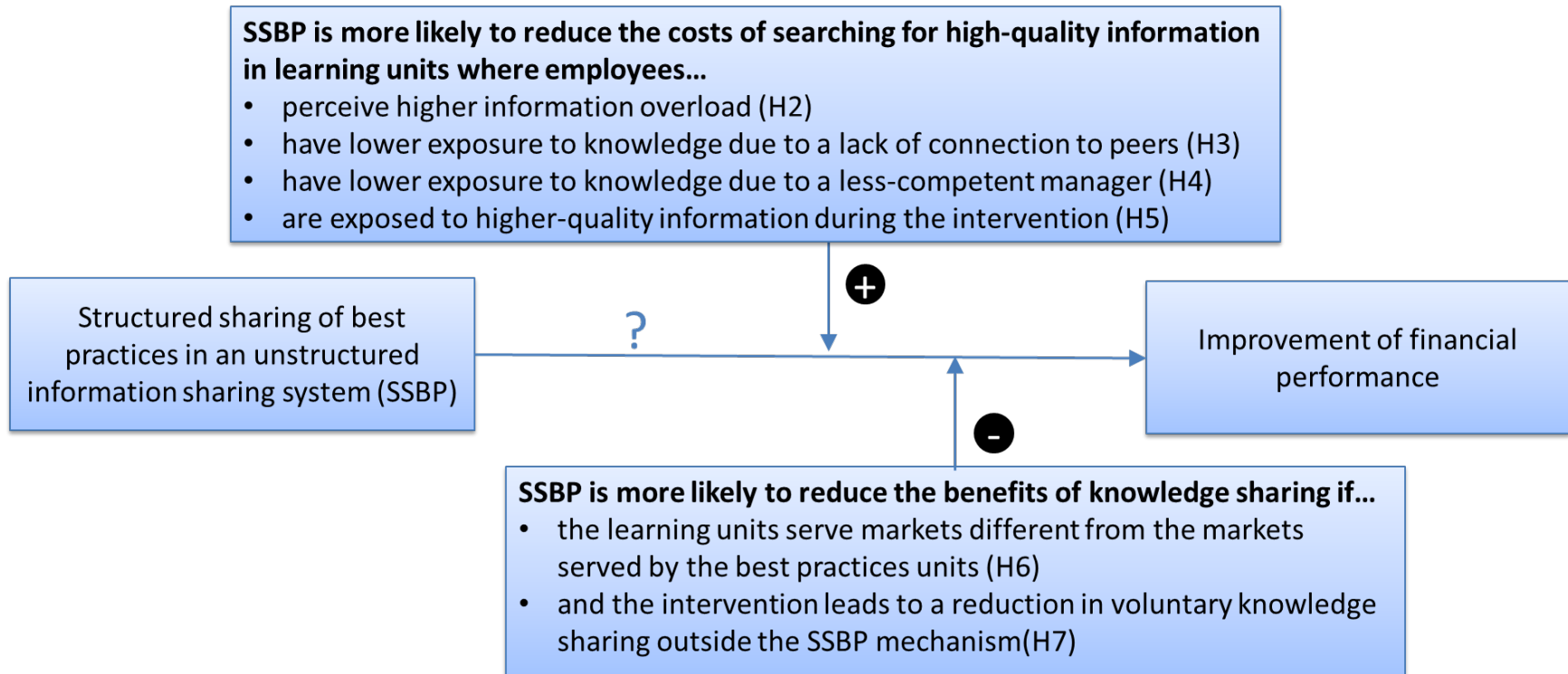
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Figure 1:

Conditions Affecting the Extent to Which Structured Sharing of Best Practices (SSBP) Improves Performance Trends



**Figure 2: Timeline**

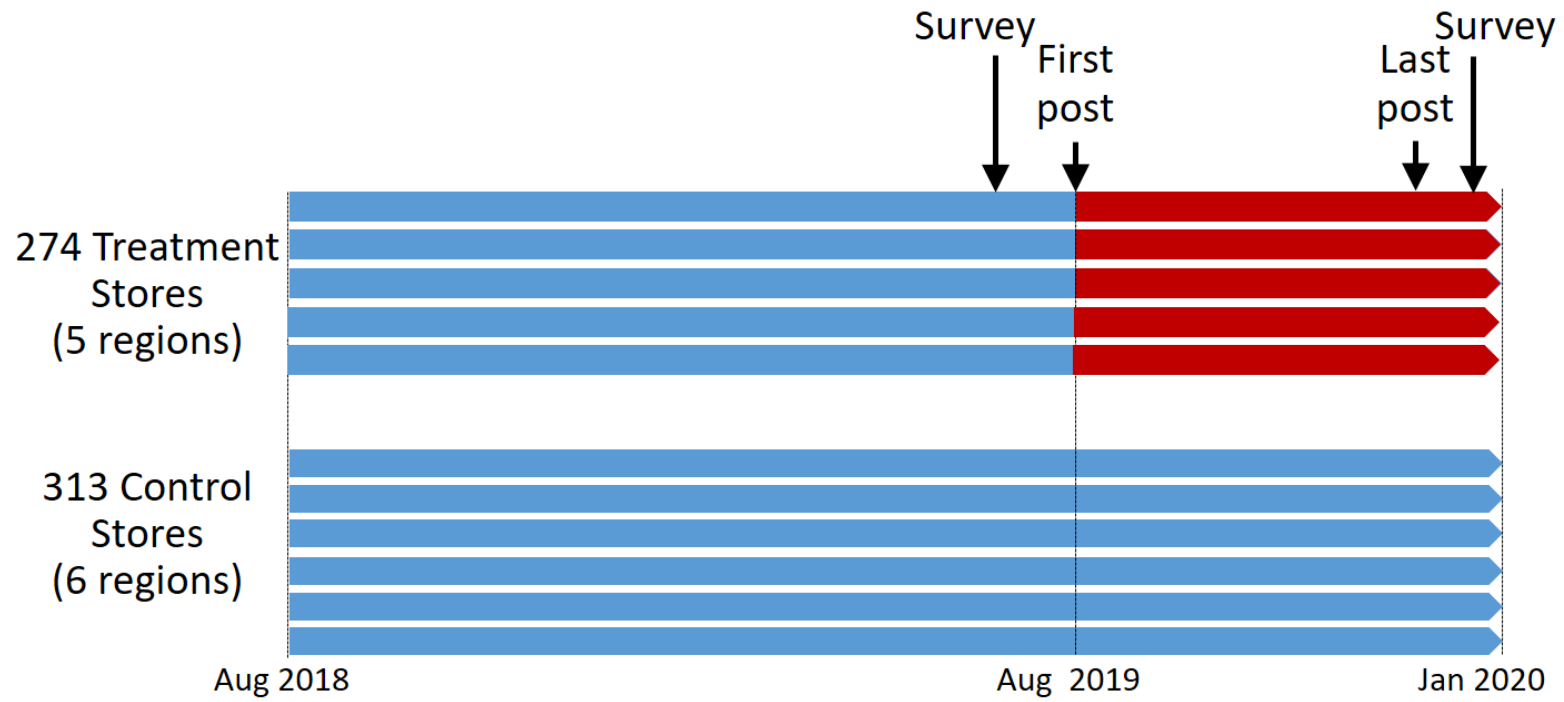


Figure 3: Best Practice Posts

Information on high performing store and store owner


Link to album

Links to best practices in five product categories

**Best Practices from Store Achieving Amazing Results at [REGION NAME].**  
[STORE OWNER]'s [STORE NAME] was one of the stores achieving the highest sales growth in 2018. [HER/HIS] team shares best practices on various ideas they are implementing this year, including ideas on fruits and vegetables, bread, dry goods, fresh products, and beverages.

**Best Practices [Firm Logo] at [Regional Group Name]**

Best Practices from [STORE NAME]  
6 Photos



**BEST PRACTICES ON BANANAS!**  
[STORE MANAGER] had a 50% increase in sales in bananas that resulted in [\$\$\$] more in gross profits.

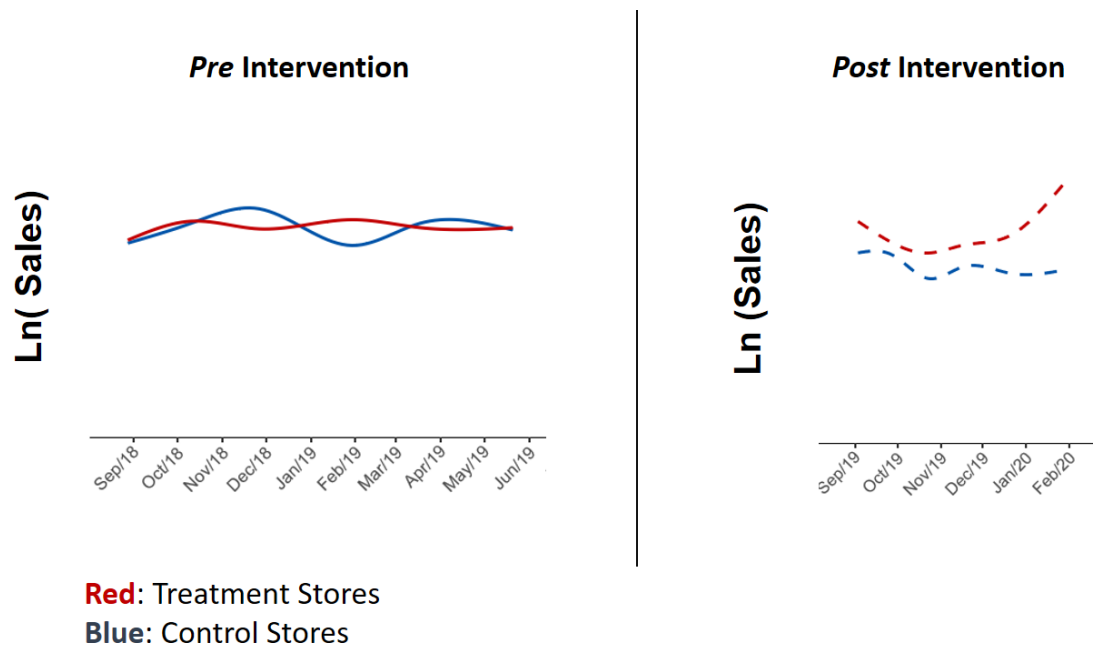
**KEY IDEA:** Before implementing this practice, the store exposed bananas facing one direction. [STORE MANAGER] rearranged the bananas so that they could be displayed on different tables, facing different directions. The bananas have not received more space in the fruit section, but their sales soared.

Title

Results

Explanation

**Figure 4: Visualization of Treatment Effects**



The vertical axis is the residual of regressing  $\text{Ln}(\text{Sales})$  on store fixed effects, week fixed effects, and store-time-trend fixed effects. The horizontal axis represents time (in weeks).

**Table 1 Randomization Strategy and Outcomes****Panel A Stratified Randomization Outcomes Allocating Treatment and Control Regional Groups within Three Sales-trend Strata**

	SSBP (treatment) group		Control group	
		# stores		# stores
<i>Low sales trends</i>	Region 1	37	Region 2	53
<i>Medium sales trends</i>	Region 3	70	Region 5	51
	Region 4	55	Region 6	68
			Region 7	68
<i>High sales trends</i>	Region 8	57	Region 10	38
	Region 9	55	Region 11	35
	<i>Total</i>	274	<i>Total</i>	313

**Panel B Covariate Balance between Treatment and Control Groups**

	SSBP (treatment) group	Control group	t-test p-value
<b>Varying by stores:</b>	274 stores	313 stores	
Gross area (square meters)	1,296.56	1,309.71	0.69
Net area (square meters)	880.16	900.82	0.36
Store age (years)	14.72	16.40	<b>0.05</b>
Average daily open hours	15.86	15.96	0.15
Weekly sales, August 2018 – July 2019 (US\$)	101,235	103,560	<b>0.00</b>
Weekly sales trend, %	0.07	0.09	0.30
Population density (2018)	520.18	327.44	0.42
Average age (2018)	39.94	39.52	0.62
Average household size (2018)	2.15	2.22	0.36
Average household income (2017) (US\$)	55,357	57,802	0.12
% with secondary(+) education (2017)	0.74	0.74	0.97
Average store counts, by municipality	20.48	11.13	0.51
<b>Varying by regions:</b>	5 regions	6 regions	
Average weekly market share held by the company relative to its competitors in a given region (2018)	24.15	23.33	0.70

**Notes:** Weekly sales and average household income amounts are converted from the local currency to US dollars. This table represents the covariate balances between the treatment and control groups after randomization but before the intervention.

**Table 2 Descriptive Statistics of Main Variables Used in the Analyses****Panel A Summary Statistics**

<i>Variable</i>	<i>Mean</i>	<i>Standard deviation</i>	<i>Minimum</i>	<i>Maximum</i>
Sales (US\$)	98,020	41,392	1,062.241	319,316
Structured Sharing of Best Practices (SSBP)	0.461	0.499	0.000	1.000
Post	0.350	0.477	0.000	1.000
Time	-16.853	23.265	- 52.000	22.000
Information Overload	3.505	0.233	3.172	3.983
# of Nearby Stores	16.742	22.193	0.000	78.000
Trust in Regional Manager Competence	- 0.079	0.543	- 1.193	0.925
Post Quality	16.506	21.361	0.000	64.857
Divergence from BP Stores	37.687	27.892	4.584	176.575
% of Posts Made in the Regional Group	0.017	0.224	0.000	17.000
% of Comments Made in the Regional Group	0.003	0.036	0.000	0.889

**Notes:** *Information Overload* is measured as the average value of the responses provided by each region's store staff to a pre-intervention survey question asking about the extent (on a scale from 1 (never) to 5 (always)) to which the statement "I am overwhelmed by the amount of information on [the ESN]" described their experience using the ESN system. *# of Nearby Stores* measures the number of same-company stores within 10 kilometers of the focal store. *Post Quality* measures the number of reactions ("likes," "hearts," etc.) to a BP post within 2 weeks of when the post was entered on the ESN, averaged across all BP posts to which a focal store was exposed over the treatment period. *Trust in Regional Manager Competence* is a principal component factor generated by three pre-intervention survey questions asking about employees' trust in their regional manager's competence. *Divergence from BP Stores* equals the average physical distance (in kilometers) between a focal store and the BP stores in the region. *% of Posts Made in the Regional Group* is the percentage of posts made by employees in a given store-week in their regional group on the ESN out of the total number of posts made by these store employees in both regional groups and store groups. The number of observations is 31,759 (store-weeks), except (a) the number of observations for *# of Nearby Stores* is slightly lower (31,704), as we lacked location information for several stores; (b) *Post Quality* and *Divergence from BP Stores* are only generated for the 14,648 treatment store-weeks.

## Panel B Correlation Tables

Variable	1	2	3	4	5	6	7	8	9	10	11
1. Log_sales	1.000										
2. SSBP	<b>-0.016</b>	1.000									
3. Post	<b>-0.038</b>	-0.001	1.000								
4. Time	<b>-0.036</b>	-0.001	<b>0.866</b>	1.000							
5. Information Overload	<b>-0.067</b>	<b>-0.090</b>	0.003	0.003	1.000						
6. # of Nearby Stores	<b>0.149</b>	<b>0.241</b>	0.000	0.001	<b>-0.430</b>	1.000					
7. Trust in Regional Manager Competence	<b>0.053</b>	<b>0.194</b>	0.004	0.004	<b>0.444</b>	<b>0.016</b>	1.000				
8. Post Quality	<b>0.116</b>	n.a.	-0.0002	0.001	<b>-0.506</b>	<b>0.945</b>	<b>-0.205</b>	1.000			
9. Divergence from BP Stores	<b>-0.201</b>	n.a.	-0.004	-0.005	<b>0.229</b>	<b>-0.675</b>	<b>-0.685</b>	<b>0.028</b>	1.000		
10. # Posts Made in the Regional Group	-0.009	<b>0.024</b>	<b>0.045</b>	<b>0.034</b>	<b>-0.020</b>	<b>-0.033</b>	<b>-0.074</b>	<b>-0.016</b>	0.010	1.000	
11. % of Posts Made in the Regional Group	-0.014	<b>0.026</b>	<b>0.046</b>	<b>0.035</b>	<b>-0.024</b>	<b>-0.042</b>	<b>-0.092</b>	<b>-0.022</b>	0.017	<b>0.777</b>	1.000

**Notes:** Correlations that are statistically significant at the 1% level are bolded. The number of observations is 31,759 (store-weeks), except (a) the number of observations for *# of Nearby Stores* is slightly lower (31,704), as we lacked location information for several stores; (b) *Post Quality* and *Divergence from BP Stores* are only generated for the 14,648 treatment store-weeks (which is why their correlation coefficients with SBBP are missing).



**Table 3 Hypothesis 1: Does an SSBP Intervention on an ESN Improve Financial Performance?**

	Dependent variable:
	Ln(Sales)
Post	-0.0270*** (-7.22)
SSBP $\times$ Post	-0.0061 (-1.05)
Post $\times$ Time	-0.0002 (-0.60)
SSBP $\times$ Post $\times$ Time	0.0020*** (4.15)
Adj R <sup>2</sup>	0.398

Note: Sample size is 31,759 (store-weeks). The regression includes store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. *Time* is the number of weeks relative to the first week of the initiative (-52 to +22).

**Table 4 Is the Performance Improvement Driven by the SSBP Intervention? Moderating Effects of Store-level Reactions to the Best Practices Posts**

	Dependent variable: Ln(Sales)			
	Stores with Fewer Reactions	Stores with More Reactions	Moderator: Store-level Reactions High	Moderator: Store-level Reactions
Post	-0.0314*** (-7.99)	-0.1010*** (-14.56)	-0.0267*** (-7.13)	-0.0419*** (-9.49)
SSBP × Post	-0.0027 (-0.36)	0.0798*** (12.65)	-0.0027 (-0.36)	0.0131** (1.96)
Post × Time	0.0002 (0.80)	-0.0089*** (-24.48)	-0.0002 (-0.51)	-0.0013*** (-3.01)
SSBP × Post × Time	0.0017** (2.42)	0.0097*** (22.11)	0.0017** (2.43)	0.0029*** (4.40)
SSBP × Moderator × Post			-0.0904*** (-23.92)	-0.0281*** (-4.99)
SSBP × Post × Moderator × Time			0.0825*** (8.51)	0.0210*** (3.05)
N	24,807	6,952	31,759	31,759
Adj. R <sup>2</sup>	0.408	0.396	0.398	0.398

Note: All regressions include store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. *Time* is the number of weeks relative to the first week of the initiative (-52 to +22). Column 1 (2) is the subsample for which stores' total reactions to the BP posts, such as "likes," are below or equal to (greater than) 2 reactions (i.e., median value for the stores with non-zero reactions, and the 75th percentile value for all stores). In Column 3, the moderator *Store-level Reactions\_High*=1 when total store reactions to the BP posts were higher than 2 reactions. In Column 4, the moderator is the total number of store-level reactions to BP posts. Post reaction measures are only generated for the treatment stores. In the full sample analyses (Columns 3 and 4), the moderator is set to zero for all control stores. As control stores have no variation in the moderator measures, *Post x Moderator*, and *Post x Moderator x Time* are dropped from these regressions due to multicollinearity between all the variables.

**Table 5 Hypothesis 2: Moderating Effects of Perceived Information Overload**

	Dependent variable: Ln(Sales)			
	Less Information Overload	More Information Overload	Moderator: Information Overload_High	Moderator: Information Overload
Post	-0.0403*** (-5.50)	-0.0176*** (-3.95)	-0.0305*** (-4.03)	-0.0268*** (-7.05)
SSBP × Post	0.0085 (0.89)	-0.0285*** (-3.62)	0.0085 (0.89)	-0.0071 (-1.21)
Post × Time	0.0011* (1.95)	-0.0005 (-1.44)	0.0015*** (2.70)	-8.5E-05 (-0.29)
SSBP × Post × Time	0.0004 (0.55)	0.0027*** (3.07)	0.0004 (0.54)	0.0019*** (3.82)
Post × Moderator			0.0049 (0.56)	-0.0019 (-0.38)
SSBP × Post × Moderator			-0.0369*** (-2.99)	-0.0065 (-1.05)
Post × Moderator × Time			-0.0023*** (-3.56)	-0.0010*** (-2.88)
SSBP × Post × Moderator × Time			0.0024** (2.12)	0.0010* (1.79)
N	14,387	17,372	31,759	31,759
Adj. R <sup>2</sup>	0.367	0.434	0.399	0.399

Note: All regressions include store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. *Time* is the number of weeks relative to the first week of the initiative (-52 to +22). *Information Overload* is the regional average value of the pre-intervention survey response to Q16 (*I am overwhelmed by the amount of information [on the ESN]*). Column 1 (2) is the subsample for which *Information Overload* is lower than or equal to (higher than) the sample median. In Column 3, *Information Overload\_High*=1 when *Information Overload* is higher than the sample median.

**Table 6 Hypothesis 3: Moderating Effects of Prior Exposure to Knowledge due to Connection to Peer Stores**

	Dependent variable: Ln(Sales)			
	Fewer Nearby Stores	More Nearby Stores	Moderator: # Nearby Stores_High	Moderator: # Nearby Stores
Post	-0.0228*** (-4.15)	-0.0325*** (-6.75)	-0.0212*** (-4.02)	-0.0283*** (-7.36)
SSBP × Post	-0.0109 (-1.30)	0.0000 (0.00)	-0.0109 (-1.29)	-0.0053 (-0.90)
Post × Time	-0.0006 (-1.40)	0.0004 (1.08)	-0.0017 (-4.24)	0.0004 (1.38)
SSBP × Post × Time	0.00301*** (4.84)	0.0007 (0.96)	0.0030*** (4.86)	0.0011** (2.24)
Post × Moderator			-0.0133* (-1.82)	-0.0054 (-0.91)
SSBP × Post × Moderator			0.0108 (0.94)	0.0069 (0.99)
Post × Moderator × Time			0.0035*** (6.69)	0.0026*** (5.46)
SSBP × Post × Moderator × Time			-0.0023** (-2.42)	-0.0012** (-2.33)
N	17,925	13,779	31,704	31,704
Adj. R <sup>2</sup>	0.411	0.425	0.400	0.402

Note: All regressions include store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. *Time* is the number of weeks relative to the first week of the initiative (-52 to +22). *# of Nearby Stores* is the number of same-company stores within 10 kilometers of the focus store. Column 1 (2) is the subsample for which *# of Nearby Stores* is lower than or equal to (higher than) the sample median. In Column 3, *# Nearby Stores\_High*=1 when *# of Nearby Stores* is higher than the sample median. In Column 4, the moderator “# Nearby Stores” is a z-score transformation of the raw measure *# of Nearby Stores* (i.e., the raw measure is mean-centered and then divided by the standard error). The number of observations is slightly lower than the full-sample size in the other tables because a few stores have missing information on their location.

**Table 7 Hypothesis 4: Moderating Effects of Prior Exposure to Knowledge due to Regional Manager Competence**

	Dependent variable: Ln(Sales)			
	Lower Trust in Regional Manager Competence	Greater Trust in Regional Manager Competence	Moderator: Trust in Regional Manager Competence _High	Moderator: Trust in Regional Manager Competence
Post	-0.0187*** (-3.61)	-0.0338*** (-6.44)	-0.0200*** (-3.47)	-0.0296*** (-7.87)
SSBP × Post	-0.0224** (-2.54)	0.0055 (0.71)	-0.0224** (-2.55)	-0.0042 (-0.73)
Post × Time	-0.0006 (-1.26)	0.0002 (0.52)	-0.0004 (-0.84)	-4.77E-05 (-0.17)
SSBP × Post × Time	0.0036*** (5.23)	0.0010 (1.50)	0.0036*** (5.24)	0.0019*** (4.09)
Post × Moderator			-0.0127* (-1.68)	-0.0142*** (-3.64)
SSBP × Post × Moderator			0.0280** (2.39)	0.0172*** (3.17)
Post × Moderator × Time			0.0005 (0.75)	0.0007** (2.14)
SSBP × Post × Moderator × Time			-0.0026*** (-2.74)	-0.0005 (-0.91)
N	13,428	18,331	31,759	31,759
Adj. R <sup>2</sup>	0.459	0.366	0.399	0.398

Note: All regressions include store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. *Time* is the number of weeks relative to the first week of the initiative (-52 to +22). *Trust in Regional Manager Competence* is a measure of the level of trust employees had in the competence of the regional manager as expressed in their responses to the pre-intervention survey. Column 1 (2) is the subsample for which *Trust in Regional Manager Competence* is lower than (higher than or equal to) the sample median. In Column 3, *Trust in Regional Manager Competence\_High*=1 when *Trust in Regional Manager Competence* is higher than or equal to the sample median. In Column 4, the moderator “Trust in Regional Manager Competence” is a z-score transformation of the raw measure *Trust in Regional Manager Competence* (i.e., the raw measure is mean-centered and then divided by the standard error).

**Table 8 Hypothesis 5: Moderating Effects of Post Quality**

	Dependent variable: Ln(Sales)			
	Lower-quality Posts	Higher-quality Posts	Moderator: Post Quality_High	Moderator: Post Quality
Post	-0.0282*** (-7.23)	-0.0282*** (-7.31)	-0.0271*** (-7.23)	-0.0270*** (-7.22)
SSBP × Post	-0.0027 (-0.38)	-0.0099 (-1.27)	-0.0026 (-0.37)	-0.0056 (-0.50)
Post × Time	0.0006* (1.89)	-0.0004 (-1.45)	-0.0002 (-0.59)	-0.0002 (-0.59)
SSBP × Post × Time	0.0005 (0.87)	0.0038*** (5.44)	0.0005 (0.88)	-0.00139 (-1.64)
SSBP × Moderator × Post			-0.0073 (-0.81)	-0.0001 (-0.05)
SSBP × Post × Moderator × Time			0.0033*** (4.35)	0.0010*** (5.65)
N	24,901	23,969	31,759	31,759
Adj. R <sup>2</sup>	0.436	0.428	0.400	0.400

Note: All regressions include store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. *Time* is the number of weeks relative to the first week of the initiative (-52 to +22). Column 1 (2) is the subsample for which post quality is lower than or equal to (higher than) the sample median. In Column 3, the moderator *Post Quality\_High*=1 when post quality is higher than the sample median. In Column 4, the moderator is *Post Quality*. *Post Quality* and related measures are only generated for the treatment stores. In each subsample analysis (Columns 1 and 2), we included all control stores. In the full-sample analyses (Columns 3 and 4), the moderator is set to zero for all control stores. As control stores have no variation in the moderator measures, *Post x Moderator* and *Post x Moderator x Time* are dropped from these regressions due to multicollinearity between all the variables.

**Table 9 Hypothesis 6: Moderating Effects of Market Divergence from the BP Stores**

	Dependent variable: Ln(Sales)			
	Less Divergence from BP Stores	Greater Divergence from BP Stores	Moderator: Divergence from BP Stores_High	Moderator: Divergence from BP Stores
Post	-0.0301*** (-7.94)	-0.0264*** (-6.64)	-0.0270*** (-7.22)	-0.0270*** (-7.23)
SSBP × Post	-0.0015 (-0.20)	-0.0107 (-1.47)	-0.0015 (-0.20)	-0.0060 (-1.02)
Post × Time	-0.0001 (-0.45)	0.0003 (1.01)	-0.0002 (-0.60)	-0.0002 (-0.59)
SSBP × Post × Time	0.0029*** (4.11)	0.0012** (2.22)	0.0029*** (4.12)	0.0020*** (4.27)
SSBP × Moderator × Post			-0.0092 (-1.03)	0.0066 (1.45)
SSBP × Post × Moderator × Time			-0.0017** (-2.15)	-0.0020*** (-5.23)
N	24,418	24,452	31,759	31,759
Adj. R <sup>2</sup>	0.429	0.428	0.399	0.400

Note: All regressions include store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. *Time* is the number of weeks relative to the first week of the initiative (-52 to +22). *Divergence from BP Stores* equals the average physical distance (in kilometers) between a focal store and the BP stores in the region. Column 1 (2) is the subsample for which *Divergence from BP Stores* is lower than or equal to (higher than) the sample median. In Column 3, *Divergence from BP Stores\_High*=1 when the store's *Divergence from BP Stores* is higher than the sample median. In Column 4, the moderator "*Divergence from BP Stores*" is a z-score transformation of the raw measure *Divergence from BP Stores* (i.e., the raw measure is mean-centered and then divided by the standard error). *Divergence from BP Stores* is only generated for the treatment stores. In each subsample analysis (Columns 1 and 2), we included all control stores. In the full-sample analysis (Columns 3 and 4), we set the control stores' moderator value to be equal to that of the minimum moderator value for the treatment stores. As control stores have no variation in the moderator measures, *Post x Moderator* and *Post x Moderator x Time* are dropped from these regressions due to multicollinearity between all the variables.

**Table 10 Does Structured Sharing of Best Practices Increase or Decrease Voluntary Inter-store Knowledge Sharing Outside the Structured Mechanism?**

	Dependent variable: Posts Made in the Regional Groups	Dependent variable: % Posts Made in the Regional Groups
Post	-0.0086 (-1.26)	-0.1780 (-1.11)
SSBP $\times$ Post	0.0602** (4.15)	0.9240** (4.50)
N	31,759	31,759
Adj R <sup>2</sup>	0.029	0.027

Note: All regressions include store, week, and store-time-trend fixed effects. Robust t-statistics in parentheses: \*, \*\*, and \*\*\* denote significance at the 0.10, 0.05, and 0.01 level. Standard errors are clustered by store. *Post*=1 if the week is or comes after the first week of the best practices initiative (August 26, 2019). *SSBP*=1 if the store is a treatment store. In Column 1 (3), the dependent variable measures the total number of posts (comments) made by employees in a store-week in their respective regional groups on the ESN. In Column 2 (4), the dependent variable measures the percentage of posts (comments) made by employees in a store-week in their respective regional groups relative to the total number of posts (comments) made by these employees on the ESN.



## **Appendix 1: Examples of ESN Posts Prior to the Structured Sharing of Best Practices (SSBP) Intervention**

These posts were randomly extracted through the ESN's Application Programming Interface (API) from the pre-intervention period. 100 observations (at the post-comment level) were extracted which, after removing the comments and posts with no text, led to the following 36 unique text posts. We asked a native speaker to translate the posts and disguise the identity of the country, company, region, store, or person. To the extent possible, we kept the literal translation of the posts.

To the best of our interpretation, "NB" means "News Blast", "F&V" means "Fruits and Vegetables".

### ***Information and Announcements***

1. **\*\* LARGE GROWTH MEASURES - WEEK 24 \*\*** New week with long weekend – Holiday X comes and gives us Monday MM/DD a day off. This in turn means bigger shopping carts and very good opportunities to tempt you to buy more and pack up your shopping cart.
2. **\*\* Opening hours during Holiday X\*\*** This poster you will find in the poster folder. Print it out and write the opening hours for your store.**\*\*NB! ON Saturday MM/DD, we close all our stores at 4pm.**
3. **\*\* \*\*NB! Pre start on activity on 30% discount on Product X\*\***  
As we earlier informed that we would run a 30% discount on Product X in week 23. Such an activity will contribute lots of customers and revenue to the store.
4. **\* New training race at F&G \* Motives for winning culture \*** - engage your colleagues and make sure everyone takes the training courses. Get the best together and win the battle to impress the customer.
5. Our company is a major contributor to the pledge to Nonprofit A through recycling bottles in store. Take a look at the film from our company's Region Y with Merchant Z.
6. Curious about products from Supplier X? Take a look here.
7. NB: Gold is down.
8. Important information - sorry for the long message. Hello everyone. Unfortunately, I have to inform you about a boring case coming on TV Channel X tomorrow Thursday. The matter has now also been picked up by Tabloid Y and we expect a publication on the web... (Author note: the post was cut off here due to the length limit of how much texts we could extract per post through the API).
9. **\*\* Governance gross week 35 \*\*** Will post every steering gross [sic] every Tuesday for the previous week. Governance gross is the theoretical gross. It is managed by national and by shop. Nationally, this gross is managed at 17.00%.
10. Product X is still at normal price ...
11. **\*\*IT'S ON: Check this weather and temperatures!\*\*** Folks, this week is on! The ones who do not follow are lost. We now know the weather for this big shopping week. It will be summer temperatures towards the middle of this week.
12. **\*\* Fruit & Green Kick off Region Y. \*\*** March 21, we gathered 300 of our great people & staked out the course to become the best at F&G within 5 years in this country! Now we drive.

### ***Congratulations and Praises***

13. **\*\* New Merchants in Region Y \*\*** We congratulate Person X, XX and XXX as new Merchants in Region Y. They have all three impressed as talents and it is with great pleasure that we welcome them on the team. Lots of luck from us at the region.
14. happy birthday to our company for 30 years in Regions X, Y, and Z!
15. Congratulations to our two talented hires – [XXX]! We cheer you and look forward to the future!

16. Region Y - Hooray!! - Congratulations to Merchant X & the team with a new fantastic store! We cheer on the whole gang and wish them a lot of luck.
17. HURRA FOR Person X 40 YEARS !!! We are celebrating our great merchant with cake and balloons today! Congratulations on the day, Person X: D: D: D Greet us all at Region Y!
18. Hip Hip Hurray... Congratulations on your 40 years! Have a wonderful celebration at Region B!
19. Congratulations on the day to all of you!!! Greetings from us at Region C!
20. Dear everyone in Team Region D, Hip, hip! how?? So much gratitude with the day.  
Have a great day with our customers with lots of smiles, laughter & surprises.  
We are looking forward to seeing their commitment, results & good atmosphere throughout.

### ***Questions about Supply***

21. Someone who has a phone number where I can reach Supplier X on? Phone number [xxxxxxxxxx] is closed for the day. We have not received the delivery yet and want to know when it may appear.
22. Hello again. Prices are fixed but need holders.
23. Hi. Does anyone have 200-300 Product X that we can find a deal on?
24. Anyone who has too much Product X? I have too little.
25. Someone with Item X they no longer use?
26. Hello everyone! We will have a barbecue party on Saturday. We need another grill. Is there anyone who has a barrel grill or other barbecue of some size to borrow?

### ***Sharing Actions***

27. \*\* LARGE GROWTH ACTION - WEEK 25 \*\*  
Week 25 brings along Holiday X at the end of the week, which means mobilizing discounts on both Fruit & Vegetables and Tex Mex towards the weekend! Be sure to have plenty of what your customers expect.
28. POS on hand terminal. We are currently working on a POS solution at the terminals together with Vendor X. Such a solution allows you to use the terminal to enter goods and put this on, for example, a customer's account.

### ***Sharing Sales Results***

29. [Happy Face] The Sunday store at 4:30pm today! And it was double as many at one point today, but could not take the picture then. Other picture shows chips at 7pm 3 hours after store opening on Sunday. It was crowded at 4pm.
30. \*\* Share figures for July - confidential \*\*  
Just under an hour ago, the share figures for Region X for July entered. Could not help but pull on the smile band [sic] when Region X was the market winner in July :) Congratulations to you all!
31. \*\*Numbers from May\*\* Hope everyone had a great celebration, even though I know many of you were in the store yesterday to prepare the store for opening today. \*\*RESPECT!!\*\* Further I am very impressed and proud of the job you've done.

### ***Other Posts***

32. Great students who want to work with us this week - post from Person C.
33. Great to get help from the kids to work at our counters.
34. Treat and admire. [with a picture]
35. Finally, the holidays are over. Calendar is open again
36. Neighborhood Y [with a picture]

## Appendix 2: Examples of ESN Posts from the SSBP Intervention<sup>30</sup>

### POST 1- BEST PRACTICES ON BEVERAGES

*Picture:* The posted picture showed a clean and organized aisle, tightly filled (from the floor to the roof and from side to side) with different types of beverages.

*Text included with the post:*

#### **Keeping Shelves Filled**

Independent of turnover at the store, this department should always be filled up. Nothing is as ugly as a poor soda department, and likewise nothing is as fantastic as a well filled-up soda-department either. There is no special risk for waste with beverages. At [STORE NAME], there is only a very small storage area for products, but beverages are the big exception. Here, we should always be able to fill up such that the department is bursting with products. It is recommended to have one person that has a little extra responsibility for restocking products here.

Even if [STORE NAME] experiences a trend where more customers want to explore the range of beer assortment, it is important to have an assortment of beer that is “correct” for the customer base. [We] use numbers and customer insights to adjust the department after the local population’s preferences.

### POST 2 - BEST PRACTICES ON BREAD

*Picture:* A picture was inserted showing an open area for bread including tall shelves arranged in an L-shape with a lower-level display in the center.

*Text included with the post:* [STORE NAME] rebuilt the bread department a couple of weeks ago. Earlier they had 2 bread fronts that made the customers have to walk around the entire disk to see the entire assortment. Now the department is more open and the customers can see more of the assortment when they walk toward the bread department.

### POST 3 - BEST PRACTICES ON DRY GOODS

*Picture:* This picture showed a highly organized aisle next to the register tightly filled with a wide variety of products such as lozenges, chewing gum, snacks, etc. The picture resembled a lengthy tightly packed duty free counter at an airport.

*Text included with the post:*

#### **See Potential at the Checkout Zone**

Here there are goods with high gross margins that could get lost if you do not prioritize this space.

- [STORE NAME] fights for the top position, with revenue of over [\$\$\$\$] only on gum/lozenges at the register zone so far in 2019. This accounts for lots of gross [sales].
- Achieve more sales area by the register by sharing/dividing the table. Smaller stores have lots to gain by taking advantage of this area.
- This is a picture of register 2, impulse fruits & vegetables are displayed in register 1

#### **Avoid Static End Aisles**

- Try to have a max. time horizon of 2-3 [weeks] at the end aisle
- Own brands have a static in/out price, but keep making changes with other products to surprise the customers, increase gross [sales], and reduce waste.
- Spend time acquiring knowledge about which items can be sold extensively.

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<sup>30</sup> With the exception of the picture in Figure 1 of the manuscript, the company’s management requested that we do not share the pictures displayed in the ESN posts for confidentiality purposes.

## **POST 4 - BEST PRACTICES ON FRESH PRODUCTS**

*Picture:* The picture of this post showed two individuals (presumably the franchise owner/store manager and the department manager of fresh goods) holding in both of their hands two ready-made dinners each, behind a cold display counter where different packets of ready-made dinners were displayed cross-sectionally in a highly organized fashion.

*Text included with the post:* The store has so far this year a +5.4% growth on fresh goods. The franchise owner and the person in charge of fresh goods plan the weekly disks together, weekday and weekend. They have had a special focus on SRDs (simple, ready dinners under [\$\$\$ price]) and ensured that there are good and simple exposures of high rolling SRD goods in the counters. The customers love it!

## **POST 5 - BEST PRACTICES ON FRUITS AND VEGETABLES**

*Picture:* Seven pictures were included in the album, featuring highly organized fruit-and-vegetable displays following the guidelines described in the text of the post (see below). Each of the pictures could be accessed through a click, and each had an explanation of how that display followed the principles shared in the main post.

*Text included with the post:*

Together with franchise owner XX and F&V responsible XX... we took some simple steps to increase growth in the department. We rebuilt the department in week 32 and positioned it according to the following principles:

1. The right item in the right place!
2. Sell more of what you sell a lot of! In other words, bring up the volume and growth of bestsellers!
3. Counter: one price per whole counter! Max two products, two prices per entire counter!
4. Priority goods on counter: High rolling goods on all counters!

Priority products we recommend for the counters:

- Avocado 2pk
- Avocado ripe single
- Mango 2pk
- Mango single
- Cherry tomatoes: our best mini-plum tomatoes [XX Name of tomatoes XX]
- Apple pink lady or current royal gala
- Sugar peas in finished bags (not by weight)
- Snack carrot
- Berries: blueberries, raspberries, strawberries
- Pointed peppers
- Sweet potatoes
- Season: berries, plums, cherries and more.