The Effect of a System for Sharing Best Practices Within Pre-existing Peer Networks

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Abstract

Peer networks, such as enterprise social networks (ESNs), can facilitate knowledge transfer across employees. However, such systems can also lead to information overload or difficulty in finding useful information. We examine data from a natural field experiment where a retailer introduced a *system for sharing best practices* (SSBP) in an existing online peer network, a control mechanism that enables easy access to well-organized best practices from high-performing units. The SSBP did not have a significant immediate or average effect on sales, however it significantly increased the sales trends of the stores where it was implemented. Sales improvement was greatest in stores that (a) perceived higher information overload from the online peer network before the intervention, or (b) had lower exposure to offline peers. The SSBP led to an increase, rather than decrease, of voluntary inter-store knowledge sharing in the online peer network. These findings shed light on how a formal mechanism for sharing best practices can enhance the decision-facilitating role of relevant information without discouraging spontaneous knowledge sharing within the existing peer networks.

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

Persistent differences in performance across units within the same organization can be largely explained by disparities in knowledge among employees (Sandvik, Saouma, Seegert, and Stanton 2020). This highlights the potential for significant performance improvements through the dissemination of best practices from high-performing to lower-performing employees. Traditionally, offline channels such as in-person peer interactions have helped employees learn from each other. However, these channels are constrained by the limits of physical interactions and the size of each employee's social network. Over the last two decades, companies have increasingly adopted new technologies, including enterprise social networks, blogs, and other similar information sharing systems, enabling broader interactions and knowledge sharing among employees. While these systems have successfully mitigated barriers to knowledge sharing, allowing a wide range of employees to share a diversity of ideas and comments at any time (Huang, Singh, and Ghose 2015), they have also led to challenges such as information overload and/or the proliferation of ideas regardless of quality, making it difficult to identify high-quality information (Levine and Prietula 2012, Bawden and Robinson 2009, Chen and Wei 2019). Consequently, many organizations and scholars are now advocating for mechanisms or systems that reliably facilitate the exchange of *high-quality* knowledge, such as best practices from high performers (Oleson 2013; Charki, Boukef, and Harrison 2018).

Research on systems for sharing best practices, however, is sparse and has yielded mixed results. Some studies have found instances where such systems were well received by employees (Al-Rasheed 2016) or even resulted in improved operational outcomes, especially in systems that included contributions not only from peers but also from experts (O'Leary 2007). Conversely, other studies have found limited benefits or outright failures due to overreliance on offline networks or a lack of motivation among high-performing employees to share best practices (Bansler and Havn 2003). Notably, little is known about the impact of pre-existing peer networks— that is, spaces where individuals connect, communicate, or naturally share information with peers—on the effectiveness of a system for sharing best practices.

Using a natural field experiment, we examine whether introducing a system for sharing best practices on a pre-existing peer network can lead to more productive knowledge sharing, reflected by a higher rate of improvement in financial performance. More importantly, we examine how online and offline peer networks may affect the effectiveness of such systems. We define a "*system for sharing best practices*" (hereafter, SSBP) as a well-organized and easily accessible formal mechanism through which high-performing units share best practices with other units on the online peer network. This involves making best-practices information held by high-performing employees available to others without imposing restrictions on sharing through other peer networks within the organization. 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).[1]

Without an SSBP, high-performing employees might share best practices in a haphazard way. They might offer only fragments of best practices—such as details of actions taken, or results achieved—at unexpected times or through any peer-to-peer channel. This makes it difficult for others to identify which practices could lead to better performance. Additionally, they might hold back from sharing because their practices might not stand out from those shared by low performers. An SSBP can address this by providing easy access to "trustworthy" best practices from

[1] This definition is similar to other definitions used in the best practices literature, which also highlight practices that have been proven successful or have led to superior performance in some unit(s) in the organization and may be applied in similar units (e.g., Havn 2003, O'Leary 2007, and Al-Rasheed 2016).

recognized high performers. It can reduce the costs of searching for high-quality information (O'Leary 2007; Oleson 2013; Charki, Boukef, and Harrison 2018). Furthermore, it can encourage high-performing units to post information in the system by providing a credible mechanism to share ideas. However, an SSBP may unintentionally divert attention from other ideas spontaneously shared through online or offline peer networks which could be more applicable to particular learning units.

An SSBP's effectiveness may depend on the online or offline peer networks through which employees in a business unit already share knowledge. We conjecture that learning units whose employees experience higher costs of finding relevant information—due to information overload from an online network or to lower exposure to an offline network of nearby peers—are more likely to benefit from the intervention. On the other hand, an SSBP might disrupt spontaneous, naturally formed peer-to-peer interactions on pre-existing networks. It could also discourage employees in units not chosen as high-performing sharing units (hereafter, best practices or BP units) from sharing valuable ideas, as they might perceive only certain types of ideas or contributions from certain units are valued by the organization.

We test our hypotheses using data from a large European chain of franchise-operated grocery stores that implemented an SSBP intervention in stores from randomly selected regions. The company already used an online peer network to promote knowledge sharing—an 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, this online peer network was overloaded with information, with hundreds of posts shared monthly across many employee groups. To help store staff more easily find valuable ideas within the ESN, the company introduced the SSBP (initially testing it in selected regions). The intervention, conducted as a natural field experiment, 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 treatment regions, two posts were uploaded every month to each regional group of the ESN, featuring best practices from two BP units in that region. These posts were structured to describe best practices by product category, using pictures and text, and linking specific actions to the results attained by the BP units. No such systems were introduced in the ESN regional group of 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 level nor a significant increase in the average treatment effect over the sample period, we find that the intervention was associated with a significant improvement in the sales *trend*, resulting in a 3.67-percent increase in sales of the treatment stores relative to the control stores at the end of the 18-week intervention. The effect was stronger for stores where employees reacted more to the best practices posts (hereafter, BP posts), indicating that the treatment effect was driven by the intervention itself, rather than some unobserved concurrent changes. The lack of an immediate sales effect may be due to the time required for employees to uncover a match between shared practices and their specific needs, adapt and implement these practices, and fully integrate them into their operations. This gradual process is consistent with the four stages of best-practices knowledge transfer documented by Szulanski (1996), reinforcing the relevance of exploring not only the immediate effects of management control systems but also lagged or trend effects that may emerge over time (e.g., Monge 1990, Erhart, Mahlendorf, Reimer, and Schaffer 2017). Our study suggests that the benefits of an SSBP expand over time rather than manifest immediately.

In assessing how pre-existing peer networks 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 online peer network (namely, the groups in the ESN) or where units had lower exposure to best-practices knowledge through offline peer interactions (measured based on the stores' natural exposure to other same-company stores). These results are consistent with the notion that the SSBP reduced employees' cost of finding useful information from high-performing peers. We also examined the possibility that the SSBP may have discouraged employees of non-BP units from posting, though our analyses revealed the opposite effect: the SSBP *increased* voluntary knowledge sharing between units.

In additional analyses, we find more positive effects where the quality of information shared was seen as higher and in units for which the knowledge shared was more relevant to their local markets, consistent with the interpretation that the SSBP led to greater improvement in financial performance through more effective knowledge sharing (rather than through enhanced efforts from employees who wanted to be recognized as BP units). Overall, these results suggest that an SSBP can improve sales trends and promote knowledge sharing, especially among employees experiencing information overload, but to a more limited degree among employees who already had a large offline peer network.

Our study enriches an emerging literature across multiple disciplines—accounting, information systems, management, and education—on the effects of knowledge sharing and, more specifically, the sharing of best practices, within online networks. Research has shown that online peer networks, such as ESNs, can drive trust and engagement among coworkers, resulting in greater knowledge sharing. For example, Huang, Singh, and Ghose (2015) and Neeley and Leonardi (2018) found that broad-based non-work information sharing builds trust among employees, resulting in greater knowledge sharing and organizational learning. Li and Sandino (2018) also found that exposure to a wide range of ideas in an online peer network designed to record creative work led to greater employee engagement and creativity in units with greater need for innovative ideas. However, other studies suggest potential drawbacks, such as lack of structure and information overload (Chen and Wei 2019), which can render many online peer networks ineffective (Bansler and Havn 2003; Neeley and Leonardi 2018). Our study sheds light on whether a formal mechanism for sharing best practices can mitigate these issues, thereby enhancing performance trends in the context of an online peer network.

Few studies have directly examined the effects of online systems that enable high-performing employees to share best practices with other employees. Existing studies point to a need for further research, particularly considering the role of pre-existing information conditions. For instance, O'Leary (2007) conducted a study where employees were encouraged to share best practices through a company intranet website curated by functional experts. This study documented improvements in operational outcomes but did not directly disentangle peer effects from functional-expert effects, nor did it explore pre-existing information conditions impacting the effectiveness of the system. Similarly, Al-Rasheed (2016) found that introducing an online portal to share peer-scored teaching best practices was well received by teachers, but this study did not assess performance outcomes. Our results generally support the notion that an SSBP can improve performance trends, consistent with the idea that an SSBP can reduce the time and effort needed to find relevant information in an online peer network. Moreover, we find that an SSBP is especially beneficial for units struggling with information overload and/or limited offline peer networks, and that an SSBP can accomplish this without discouraging knowledge sharing elsewhere in the online peer network.

More broadly, we contribute to the accounting literature on management control systems as decision-facilitating tools, which help direct employee attention to information that could improve decision-making 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. Similarly, Manthei, Sliwka, and Vogelsang (2023) demonstrate that providing decision-facilitating information can significantly enhance profitability by directing managerial attention, even though the interplay with performance pay does not always yield complementary effects. However, Eppler and Mengis (2004) and Casas-Arce et al. (2017) highlight a potential challenge—systems containing overly detailed information could degrade performance through information overload. As information-sharing systems become more prevalent, increasing employees' exposure to detailed information, it becomes crucial to understand what management controls can reduce the costs of searching for and processing valuable information. Our study sheds light on how an SSBP mechanism within a broad-based information-sharing system can enhance the decision-facilitating role of relevant information in today's world of (over)abundant information. Finally, our research provides insights on ways to leverage information sharing systems to promote productive employee interactions and the exchange of ideas, especially in the face of increasing information overload—an issue of growing concern for managers and entrepreneurs. To the best of our knowledge, this 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 a System for Sharing of Best Practices

Although modern information sharing systems, such as ESNs, have significantly expanded network channels for peer-knowledge exchange, awareness of work-related best practices continues to vary significantly across employees (Sandvik et al. 2020). Prior research has suggested that these novel online peer networks can improve knowledge sharing (Lam, Yeung and Cheng 2016; Aboelmaged 2018), but 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). Many of these information systems are broad-based and have minimal restrictions, allowing any user to share information at any time or "location," in any format or group in the system. The varying quality of the information supplied and the high costs of searching for relevant content can limit the benefits promised by these peer networks. 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 system with low-value or even frivolous posts, just to be noticed (Oettl et al. 2018). From an information demand perspective, employees who could benefit from learning about best practices often find the search time-consuming and/or unproductive (Levine and Prietula 2012), as these online peer networks are often overloaded with information irrelevant to the needs of their users.

Scholars and practitioners increasingly recommend adding formal mechanisms to these information sharing systems to facilitate the structured sharing of best practices, enhancing *productive* knowledge exchange and learning (Oleson 2013; Charki, Boukef, and Harrison 2018). A system for sharing best practices (SSBP)—a management control mechanism that involves high-performing units periodically sharing best practices in an organized manner—can potentially address the aforementioned information supply and demand problems. An SSBP can motivate high performers to share their knowledge by formally recognizing and legitimizing their distinctive practices and/or offering them an opportunity to help others.[2] It can also ensure that best practices are clearly communicated and made accessible, serving as a decision-facilitating mechanism for employees demanding high-quality knowledge to make timely, informed decisions (Demski and Feltham 1976).

In sum, an SSBP enables units to (a) more easily uncover and access valuable knowledge by directing their attention to high-quality ideas, (b) trust those ideas, as they come from verified high performers,[3] (c) understand those ideas, through clear descriptions linking actions to results, and (d) reduce the costs of searching for relevant knowledge in an environment prone to information overload. Note that, while the main purpose of introducing an SSBP is to improve performance, it is likely that such a system will not have an immediate effect once implemented. The process of transferring knowledge can take time, as it needs to go through four stages (Szulanski 1996): (1) *Initiation*, which consists of uncovering a match between a shared practice and a learning unit's need to apply that particular practice. When an SSBP is first implemented, this process may take even longer as the number of shared practices will initially be low and will only accumulate over time. (2) *Implementation*, which occurs once employees in a learning unit have decided to adopt the practice in their unit. This stage may require investment and adaptation of the original idea to the learning unit. For example, in a retail setting it may require rearranging or purchasing fixtures to implement a new display; acquiring new products; deciding how to implement an idea originally applied to one product, to a different product; or assigning new responsibilities to employees. (3) *Ramp-up*, where the new idea is applied, and any unexpected problems are identified and

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[2] 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).

[3] 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). Furthermore, they are more likely to benefit from knowledge shared by top performer employees (Sandvik et al. 2020).

corrected. (4) *Integration,* where the learning unit can fully incorporate the new knowledge and experience performance improvements. As a result, the benefits of an SSBP typically expand overtime as more best practices are shared and gradually adopted, leading to a more positive performance trend.

An SSBP, however, is not guaranteed to improve knowledge sharing and performance. It could have no effect or even backfire if (a) high-performing units do not know which key actions led to their success and, consequently, have no clarity on what useful practices to share (Hanna, Mullainathan, and Schwartzstein 2014); (b) internal competition and fear of giving away relative advantages discourage high-performing units from sharing their best ideas (Butt, Antia, Murtha, and Kashyap 2018; Li and Sandino 2018); (c) learning units find the shared practices no more useful than those already available through pre-existing online or offline peer networks; (d) learning units do not find the new ideas applicable or are unable to replicate them due to time, ability, or resource constraints (O'Dell and Grayson 1998); (e) learning units fixate on the limited set of ideas featured in the SSBP intervention, ignoring other relevant ideas shared through other offline or online peer networks; or (f) non-BP unit employees are dissuaded from sharing their own ideas through online or offline networks because the SSBP may diminish their intrinsic motivation to do so (Lam and Lambermont-Ford 2010). These considerations underscore the nuanced role that pre-existing peer networks play in the effectiveness of an SSBP.

Given the competing possibilities, we state Hypothesis 1 in the null form:

Hypothesis 1: An SSBP will have no effect on a business unit's performance improvement.

2.2. Effect of Peer Networks on the Effectiveness of an SSBP

In this subsection, we examine the extent to which the characteristics of pre-existing online and offline peer networks affect the impact of an SSBP on performance trends.

2.2.1. Impact of Pre-existing Online Peer Networks on the Effectiveness of an SSBP

As previously mentioned, we conjecture that units will benefit more from an SSBP when they are otherwise overloaded with information from a pre-existing online peer network. Research suggests that information helps employees improve their decisions and performance up to a point, beyond which information overload—"too much information"—causes 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 volume of information exceeds an individual's capacity to process it (in terms of time and ability). This undermines the intended decision-facilitating role of online information sharing systems, which have proliferated over the last two decades.

We expect that an SSBP will help employees who perceive an overload of information through these online peer networks by (a) reducing their need to process large amounts of data to find valuable information and (b) improving their ability to process the given information. Furthermore, search costs caused by information overload are often attributed to variations in the overall quality or usefulness of the available information (Eppler and Mengis 2004). Prior studies show that increasing information quality can reduce perceptions of information overload (Simpson and Prusak 1995). An SSBP is designed to improve information quality and reduce perceived information overload because it features best-practice knowledge from verified high-performing units, linking actions to results. This makes information easier to understand and more relevant for decision-making (Gorla et al. 2010). We therefore hypothesize:

Hypothesis 2: The effect of an SSBP on performance improvement will be more positive in units whose employees perceive higher information overload in the pre-existing online peer network than in units whose employees perceive lower information overload.

2.2.2. *Impact of Pre-existing Offline Peers on the Effectiveness of an SSBP*

Geographic distance affects connections among peers in both offline and online social networks. Studies have shown that geographical clusters promote networking among nearby units and increase the diffusion of knowledge (Baptista 2000; Bailey et al. 2018). Moreover, while online information sharing systems can overwhelm isolated users, those with a network of trusted peers find them more manageable. Trusted peers can provide valuable guidance within the online network by forwarding posts related to best practices and/or sharing their experiences and opinions on those practices. In contrast, employees in units far from other same-company units have fewer opportunities to build social networks, resulting in lower knowledge acquisition (Singh, Hansen, and Podolny 2010). Without an SSBP, employees from geographically isolated units may struggle to find relevant knowledge, whether offline or online. An SSBP could address this by highlighting the most useful information for these users, reducing their costs of finding relevant information.

Nevertheless, it is still possible that units located closer to other units might benefit more from the SSBP if the *content* of the best practices shared is difficult to understand and discussions with peers from nearby units could help employees better adapt best practice ideas in the system to their own context (Audretsch 1998). Despite this, we expect that isolated units will benefit more from the SSBP, given that it is designed to be well organized and self-explanatory. Thus, we hypothesize:

Hypothesis 3: The effect of an SSBP on performance improvement will be more positive in units located farther from other same-company units than in units located closer to other same-company units.

2.3 Changes in Voluntary Knowledge Sharing Outside the SSBP Mechanism

In addition to changing employees' access to high-quality knowledge, an SSBP could also alter the natural patterns of interaction among peers in the pre-existing online network. A potential negative consequence of an SSBP is that it might reduce the natural motivation non-BP unit employees have to share their own ideas and practices voluntarily. Research identifies several factors that motivate employees to share knowledge in offline or online peer networks, 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 Faraj 2005). An SSBP could weaken these motives for non-BP units for three reasons. First, it could crowd out altruistic and reciprocity motives if employees perceive that their responsibility and autonomy to share knowledge has decreased (Lam and Lambermont-Ford 2010). Second, it could reduce feedback and recognition if these benefits shift to the BP-unit employees featured in the SSBP. Third, it could make non-BP unit employees worry that their shared content will be judged unfavorably against the high-quality practices shared by the BP units.

While it is possible that an SSBP could instead *increase* posts from non–BP-unit employees by modelling constructive ways to create and share information, we expect that an SSBP will decrease the number of voluntary posts for the reasons explained above. We therefore hypothesize:

Hypothesis 4: The SSBP will lead to lower voluntary sharing of information in the online peer network outside the SSBP mechanism.

III. RESEARCH SETTING AND INTERVENTION

3.1. Research Setting

Our research setting is a large grocery store chain that implemented an SSBP in one of the countries where it operates. Each franchisee owned exactly one store and kept the residual profit of that store after paying a royalty to the company.[4] 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—the franchisees' actions.[5]

The company had implemented an ESN for peer-to-peer communications a few years before this study began. Any employee using the ESN could, at any time, form groups; create and share posts or photo/video albums; comment on posts; "like" or react to posts with symbols (e.g., a "heart" or a "happy face"); and send public or private messages to others. At the beginning of 2019, more than 85 percent of employees were active in the ESN. 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, which were two of the most accessed groups on the ESN. Appendix 1 shows randomly selected ESN posts from this time. Information on best practices was often incomplete and scattered, buried within a large volume of information. Most posts were announcements (related to marketing, operations, or training) or congratulatory messages celebrating an employee's or a store's achievements or anniversaries). Stores also posted requests

[4] 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.

[5] 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.

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 having any discussion about results. None of these randomly selected posts described both (a) recommended practices *and* (b) the results linked to those practices.

To promote productive knowledge sharing and improve performance, the company pilot-tested an SSBP in 2019. In the country where we conducted our study, the retail company had over 600 stores across 12 regions, with an office overseeing each region. Before the study, one regional office had already trialed an initiative on the ESN promoting best practices among its stores. Further development of this initiative resulted in the SSBP intervention, which was then introduced in five additional regions (while the remaining six regions continued using the ESN as usual, without the SSBP). The HR team, which managed the ESN, implemented this SSBP as a natural field experiment. We were able to draw causal inferences, thanks to the random selection of the treatment stores, and to examine the effects of the SSBP in a natural context (Bandiera et al. 2011, Floyd and List 2016). Since the subjects were unaware that they were participating in a study, we could rule out self-selection or a "Hawthorne effect" as alternative explanations for our results. The company provided our research team with the resulting data for analysis.

3.2. Randomization

The researchers (we) used a stratified randomization strategy to select treatment regions. The 11 regions used to test the SSBP were split into three strata based on store-level weekly sales trends over the 12 months before the intervention, with regions 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" due to frequent interaction between employees (Regions 2 and 8) into the same (treatment) group. Panel A of Table 1 shows the allocation of regions and stores into treatment and control groups.

To uncover the potential benefits of the SSBP, the company focused the intervention on five product categories: fresh goods (23.3% of sales), dry goods (19.5%), beverages (11.9%), fruits and vegetables (11.5%), and bread (4.7%). These categories accounted for most of the sales.[6] 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 using simulated sales data from the previous 12 months.[7]

Given the relatively low number of clusters (11 regions), we could not expect *all* confounding variables to be equally distributed in the treatment and the control groups. To ensure comparability, 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). The only statistically significant differences were that treatment stores tended to be younger and had lower levels of sales (although not lower sales trends)[8]. These differences were controlled for in our regression analyses.

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[6] As we will describe later, information about best practices was collected and organized by the regional office for each selected category to ensure the quality and consistency of the intervention; thus, the more categories covered, the greater the effort and cost.

[7] 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 (α=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.

[8] In Panel B of Table 1, "weekly sales trends" shows no statistically significant difference between the control and the treatment groups. In untabulated analyses, using the pre-intervention data, we regress the dependent variable (log sales) on our time trend variable (*Time*) and an interaction term of *Time* and our treatment indicator (*SSBP*) along with

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 ESN groups. According to the HR managers, these posts remained available on the albums of the ESN regional groups after December 31, 2020. None of this was done in the six control regions. Figure 1 shows the intervention timeline.

Corporate HR and the regional managers collaborated to select eight high-performing stores from each treatment region, to be featured during the SSBP intervention. Selection was based on proprietary information (including profitability measures and some "soft" information) which was inaccessible to us.[9] Every month, two selected stores from each region were featured in BP posts two weeks apart. Each post was pinned to the top of its regional group on the ESN for two weeks until the next BP post replaced it. After being unpinned, all BP posts were kept in the group's archive (accessible to all store teams in the region).

To maintain consistency in the SSBP intervention across regions, sales managers from each treatment region followed a protocol. Each month, they visited the selected high-performing best-practices stores (or BP stores), recorded the best practices highlighted by the store manager in the

fixed effects, finding that the coefficient on the interaction term to be statistically and economically *insignificant*, suggesting no difference in the time trends between the control and the treatment groups prior to the intervention.

[9] Untabulated analyses show that the likelihood of a store being selected in a treated region was significantly correlated ($p<=0.01$) with the performance measure that we used in our study (log sales) as measured in the pre-intervention period. Part of the company's reason for including "soft" information in the selection (rather than completely basing the selection on objective sales measures) was to consider whether a store would be known or perceived by its peers as high performers. Regarding the implementation of the 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. Although the SSBP significantly reduced the cost for the high performer to share the BP information, neither the regional managers nor the regional sales managers could force or pressure the stores to share.

five featured product categories, and did a "walk-through" with the store manager to take photos and videos. Afterwards, these regional sales managers created the BP posts for the regional ESN groups—with texts, photos, and/or videos—in the form of an album, with the same predetermined structure across all treatment regions (see Figure 2). 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 shows representative BP posts. The vast majority presented appealing photos of product displays with an explanation of why the store staff designed them that way and the results obtained.[10] Some posts emphasized the relevance of empowering employees to take 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 seemingly 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, assuming customers would seek them out wherever they were placed. This

[10] Note that although the store managers attributed their higher performance to these shared practices, the company does not know for sure (e.g. through rigorous statistical tests) whether their high performance was due to the specific "best practices" they shared.

reflected different perspectives on what constituted best practices, potentially reflecting local customer preferences.[11]

The BP posts received a fair amount of attention. Within each treated region, we tracked the "likes," comments, and views for each BP post. On average, within two weeks, a BP post received 33.5 "likes" (up to as many as 100) and was seen by 489 users (up to as many as 830). During the entire post-intervention period, a typical BP post received approximately three comments while a typical non-BP post received 0.49 comments.

3.4. Pre-intervention Survey

The company conducted a pre-intervention survey to gather data about the employees' experience at work and use of the ESN, including their perceptions of information overload in the ESN. Employees from 491 stores in the 11 regions we analyzed responded.[12] Eighty-five percent indicated that they had used the ESN for more than five minutes a week over the past two months.

The pre-intervention survey results suggested that employees appreciated the ESN's information. Using a Likert scale in which 1 = never, 2 = rarely, 3 = sometimes, 4 = very often, and 5 = always, employees responded, on average, "very often" (mean=3.8, median=4) to the statement "*The information on [the ESN] helps me do my job better.*" For employees applying ideas found on the ESN, the top three characteristics of the ideas they adopted were that they were (a) creative or

[11] An alternative explanation is the possibility that what some high-performing stores consider "best practices" are not really the causes for their success. This would work against finding results (i.e. the effects of the SSBP intervention might be even stronger than the results documented in the paper if all best practices were empirically validated, however this kind of validation is unusual in practice).

[12] 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.

novel (36% of responses); (b) posted by individuals who had already generated positive results (29%); and (c) easy to copy (13%). [13]

Despite this, we also confirmed the concerns that led management to implement the SSBP. Using the same Likert scale, respondents replied, on average, with "sometimes" to "very often" (mean=3.5) to the statement "*I am overwhelmed by the amount of information on [the ESN].*" We used the response to this question as a measure of information overload (Cai and Sun 2018). Furthermore, to validate this measure of information overload, we conducted a correlation analysis of this measure with responses to the statement "*It's easy to find the information I need on ESN*" (correlation coefficient: -0.27, significant at the 1% level). This suggests employees experiencing information overload were *less* likely to find useful information in the ESN, consistent with arguments leading to Hypothesis 2.

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 the period from August 1, 2018 to the start of the intervention in August 2019 as the pre-intervention period (Post=0) and from the last week of August to the end of January 2020 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-

[13] *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.

intervention 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.[14,15] 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.[16] Observations from the treatment group account for 46 percent of the store-week observations.

To test Hypotheses 2 and 3, we constructed two moderating variables: *Information Overload* and *# of Nearby Stores*. Later, we turn each moderator into (a) a dummy indicating whether the underlying raw measure was above the sample median and (b) a continuous version of the measure *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

[14] 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.

[15] 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.

[16] 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.

peers from same-company stores. The average number in our sample is close to 17; it ranges from 0 to 78. In Table 6, we normalize the continuous version of the measure for ease of interpretation, i.e., we subtract the mean from the raw measure (*# of Nearby Stores*) and divide it by its standard deviation.

In Panel B of Table 2, univariate correlations show that sales on average were lower in the post-intervention period, possibly due to cyclicality. Stores in the 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), but negatively and significantly correlated with perceived information overload, consistent with the notion that the conditions in online and offline peer networks could have explained variation in unit-to-unit knowledge sharing. Being in the SSBP treatment group 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 an SSBP

First, we visualize the treatment effect of the SSBP on financial performance by plotting the adjusted natural log of weekly sales (*Ln(Sales)*) against time, contrasting the treatment and control groups.[17] In Figure 3, the horizontal axis represents time (in weeks) while the vertical axis is the

[17] Like Deller and Sandino (2020), we assess the effect of the system intervention (SSBP) on the natural logarithm of sales because we aim to analyze the effect of SSBP on the percentage change in sales, given that the initial level differed across stores. In untabulated analyses we verify that our results are robust to using raw sales as the dependent variable.

residual of regressing *Ln(Sales)* on store fixed effects, week fixed effects, and store-time-trend fixed effects.[18] Prior to the SSBP intervention, the treatment and control groups exhibited similar sales trends, as we had ensured during randomization. Following the 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 expectation that the effect of knowledge sharing associated with SSBP is best captured by a sales-trend effect (rather than an average treatment effect on sales level), given the time stores require to uncover and adapt new ideas (refer to the four stages for transferring knowledge in section 2.1).

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:

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

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);[19] and $SSBP_i = 1$ if store i is a treatment store. The main focus of our estimation is the *sales-trend effect* (δ_5); that is, the change in sales relative to that of control stores for each passing week since the beginning of SSBP. Therefore, $\delta_2 + \text{Time}_t * \delta_5$ will be the total *Sales Effect as of Time t*; that is, the change in sales relative to that of control stores by

[18]In untabulated analyses we replicate Figure 3 including 95% confidence intervals and find a separation not only of the average trend but also the confidence intervals towards the end of the sample period (i.e., January of 2020).

[19] 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.[20] Due to the store, week, and store-trend fixed effects, many control variables that do not have enough variations (e.g. time-invariant store characteristics) are not included as they would be subsumed. 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 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 the SSBP on sales and on the sales trend.[21] 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, δ_5 (the coefficient for $SSBP \times Post \times Time$) is positive and significant at the 5% level, indicating that SSBP had a positive and statistically 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.[22] Our results show that the SSBP

[20] 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 β4 and β5 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 x Post x Time*).

[21] 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).

[22] The intervention's total effect ($e^{(-0.00614+0.002*18)} - 1$), including the immediate effect and the gradual improvement 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.

improved the financial performance trend.[23,24] The effect took some time to manifest, consistent with the nature of the SSBP and the outcome being a performance trend. This is consistent with Szulanski's (1996) description of the stages it takes to see results from knowledge transfers: "the recipient is likely to use the new knowledge ineffectively at first, but gradually improves performance, ramping up towards a satisfactory level." The SSBP's significant effect on stores' sales trends are robust to excluding the 36 BP stores, as are all subsequent results reported below.

To make sure that the observed effect was driven by the intervention, rather than by concurrent confounding factors of which we were unaware, we also examine whether the positive treatment effect is stronger for the stores that reacted more to the BP posts. Specifically, in Table 4, we re-ran the baseline regression in the two subsamples resulting from splitting the stores based on 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* × *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 by some stores 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

[23] 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.

[24] In untabulated analyses restricting the sample to stores without franchisee turnover we found that our results on the treatment effect (Hypothesis 1) still hold. We also conducted a robustness test where we ran a standard difference-in-differences regression including *region x month* fixed effects (instead of estimating differential time trends between control and treatment groups) to explicitly control for factors that vary across regions over time. We find that the treatment regions experienced a statistically significant and positive average treatment effect on sales relative to the control regions, consistent with the positive total effects documented in footnote 22.

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 19.08-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 this intervention of sharing best practices that drove the effect on sales improvement.

4.3. Factors Moderating the Effectiveness of the SSBP

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

Hypothesis 2: Perceived Online Information Overload

To test Hypothesis 2, we use perceived information overload as the moderator. Although perceived information overload is a measure from the pre-intervention survey, it represents an *ex ante* condition exogenous to the implementation of SSBP. A t-test on *ex ante* information overload between the treatment and control groups shows no statistical difference (t-stat = 0.36). 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 the 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 × Post × Moderator × 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 online information overload in the ESN prior to the intervention.[25]

Hypothesis 3: Exposure to Offline Knowledge from Peer Stores

To test Hypothesis 3, we use *# of Nearby Stores* as the moderator. Prior to the SSBP, employees in stores with fewer nearby same-company stores were less likely to have an offline network of peers that would either share ideas with them or help them identify scattered best practices in the ESN, and were therefore likely to find the 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, the SSBP had a positive and statistically significant effect on the sales trend (0.00301; that is, after 18 weeks, the SSBP was associated with a sales-trend effect explaining 5.57-percent-higher sales in the treatment group relative to the control group). In contrast, the 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 × Post × Moderator × 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

[25] 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. In untabulated analyses, we included *both* moderators' interaction terms in one regression and found that the coefficients on the quadruple interaction terms (*SSBP x Post x Moderator x Time*) remain similar in magnitude and statistical significance. This mitigates some concerns of multi-collinearity between the moderator variables.

an offline network of nearby peers.[26] The results in Table 6 are consistent with Hypothesis 3: learning units with fewer nearby same-company stores experienced greater sales improvement.

4.4. Hypothesis 4 - Effects of SSBP on Voluntary Inter-store Knowledge Sharing

To test Hypothesis 4, Table 7 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) and the percentage of posts shared by store employees in the regional groups (relative to the total number of posts shared by store employees; see Column 2). 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.[27]

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 sharing content with other stores on the ESN, SSBP triggered more of it, consistent with the notion that the intervention may have highlighted productive ways of sharing practices. We find no significant decrease in the number or percentage of posts shared by employees in any treated region.

4.5. Further Analyses: is the effect driven by knowledge transfer?

Was improved performance due to the transfer of best practices knowledge, or an increase in employee motivation to gain recognition as a "best practice" store? If it was due to store

[26] Results are similar when we define "nearby stores" as stores within 5 or 3 kilometers.
[27] 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.

employees' motivation to gain recognition as a future BP store rather than due to the passing of useful knowledge, we would have expected to see an immediate sales increase. Instead, our results show a gradual sales improvement, consistent with knowledge transfer rather than motivation to exert greater effort to gain recognition.

To further test this mechanism of knowledge transfer, we conducted three additional analyses to examine whether the treatment effects varied with the content of the posts (namely, with the product categories included in the posts, the quality of the posts, and the relevance of the shared best practices).

Product Categories Featured in the BP posts

If our results were due to employees' motivation to gain recognition rather than knowledge transfer, we would observed an increase in effort 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 and would not be reacting to the content of the posts but to the incentive to be featured). In untabulated results, we use the same model (as in Table 3) and test whether the intervention had a similar effect on sales of the 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 δ_2 nor δ_5 was 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.

Quality of Shared Knowledge

Table 8 Panel A 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*). 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)[28].

In Columns 1 and 2 of Table 8 Panel A, 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* × *Post* × *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 7.08-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* × *Post* × *Time*), finding that the difference in the sales-trend effect between the subsamples is statistically significant.[29] 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* × *Post* × *Time*), indicating that the sales-trend effect of SSBP becomes stronger as the quality of BP posts increases.[30] This is consistent with access to useful knowledge being a mechanism driving the positive effect of SSBP on sales trends.

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[28] Although the stores in our setting are independent franchises and do not compete for corporate resources, there remains some possibility of competing for customers and the potential for BP stores to share less valuable information as a result. However, our post quality measures are positively and significantly correlated with the number of stores within a 10-kilometer radius of a BP store, suggesting that in this setting, having more stores close to the BP store is associated with *higher* quality of the shared information, rather than lower quality.

[29] Notice that in this 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.

[30] We replicated the analyses 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 Panel A: our sales-trend effect is driven by posts receiving more comments.

Relevance of Shared Knowledge

In Table 8 Panel B, we use distance from the learning unit 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. *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 Table 8 Panel B, 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.[31] 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 (i.e. where the shared knowledge is more relevant). The magnitude of the coefficient (0.0029) for the low-divergence (i.e. "high-relevance") subsample (Column 1) suggested that, by the end of the 18-week intervention, the SSBP sales-trend effect resulted in 5.36-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 where the knowledge is less relevant (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. Although learning units serving different markets than the BP units could have found the shared best practices more novel, in fact they experienced smaller sales growth following the SSBP intervention as the shared knowledge

[31] In Panel B, as in Panel A, 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.

was less relevant to them. This is consistent with the transfer of useful knowledge being the main mechanism behind the treatment effect (rather than an increased level of motivation or efforts).[32]

V. CONCLUSION

We use data from a natural field experiment in a large retail chain to examine the effects of introducing a system for sharing best practices in an existing online peer network (specifically, an ESN). 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 an SSBP being conditioned by existing online and offline peer networks, the effect was more positive in stores whose employees perceived more information overload using the online peer network prior to the intervention, and in stores with *less* guidance from an offline network of peers for uncovering best practices. In addition, we find evidence that the SSBP had a positive spillover effect, increasing (rather than decreasing) voluntary inter-store knowledge sharing outside the SSBP mechanism. Overall, these results suggest that an SSBP can improve sales, but that such results depend on the conditions of individual units.

While our results are robust to alternative specifications, they should be interpreted with caution. First, because the company implemented the intervention following the protocol of a natural field experiment, it faced limitations that may have reduced the power of the tests. For example, to ensure consistent treatment quality, regions or stores were not allowed to customize the structure of the BP posts. Additionally, although the BP posts were not intended to be shared outside their

[32] 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 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.

respective regional groups in the ESN, and the company took measures to minimize "contamination" risks by assigning regions that were likely to communicate with each other into the same treatment or control group, we could not completely track if SSBP content was saved and shared with control group members. This could have led to an underestimation of the intervention's effect. Second, the "best practices" shared through the SSBP were selected by high-performing BP unit managers but were not centrally validated. Thus, these practices were not necessarily optimal and could have had negative "spillover" effects, such as a promotion that could have increased sales in one store while decreasing sales in nearby stores. Despite this, the SSBP was associated with a positive sales trend, suggesting BP units generally identified value-creating practices. Third, certain features of the field site may limit the generalizability of our findings. For example, the unit (store) managers in our setting were franchisees who had no obligation to participate in the intervention, but they had strong incentives to create value from useful information shared in the ESN. Although many online peer networks such as ESNs are prone to information overload (due to the typical features of real-time communication and unrestricted peer interactions), not all such networks necessarily experience this issue. However, our findings likely generalize to any intervention consisting of sharing information from high-performing units within an existing ESN or similar online peer networks, provided employees are motivated to improve performance. Fourth, while system records show that stores continue to access and react to the BP posts shared during the intervention (even stores that opened after the intervention), the long-term learning effects of the SSBP (beyond the 18-week period we analyzed) remain unclear due to the duration of the intervention and the limited data availability after the onset of the COVID-19 pandemic. Future research can explore the effects of longer interventions, as well as how an SSBP, a formal and structured mechanism, and spontaneous information sharing on the peer network complement each other and co-evolve over time. Finally, we provide evidence that an SSBP can result in gradual performance improvements through valuable content dissemination, particularly benefiting units previously experiencing online information overload or limited exposure to best practices. Future studies could examine the effects of varying the frequency of sharing best practices, building on studies like Casas-Arce, Martínez-Jerez, and Lourenço (2017), investigate different formats for organizing best practices, or isolate the effects of structuring information alone.

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Figure 1: Timeline

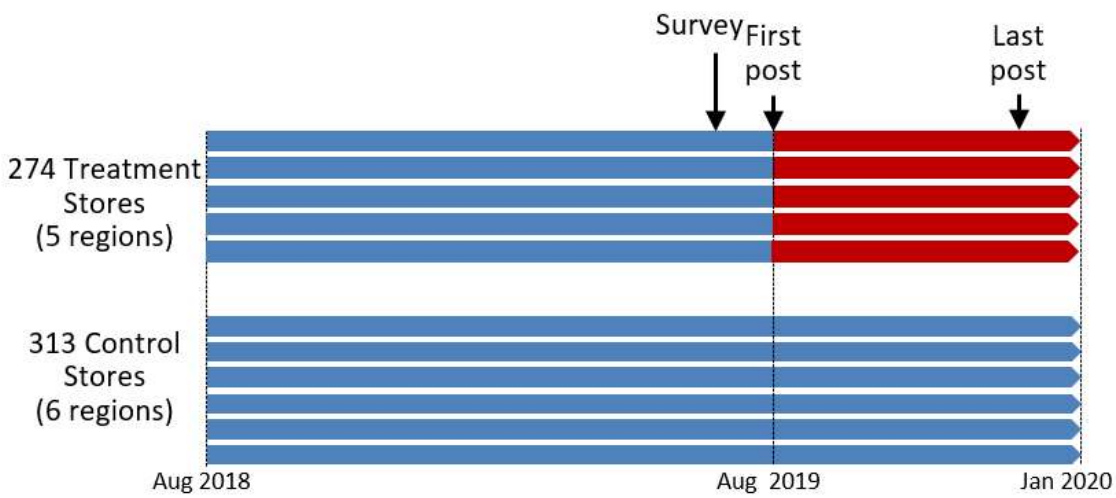


Figure 2: Best-practice Posts

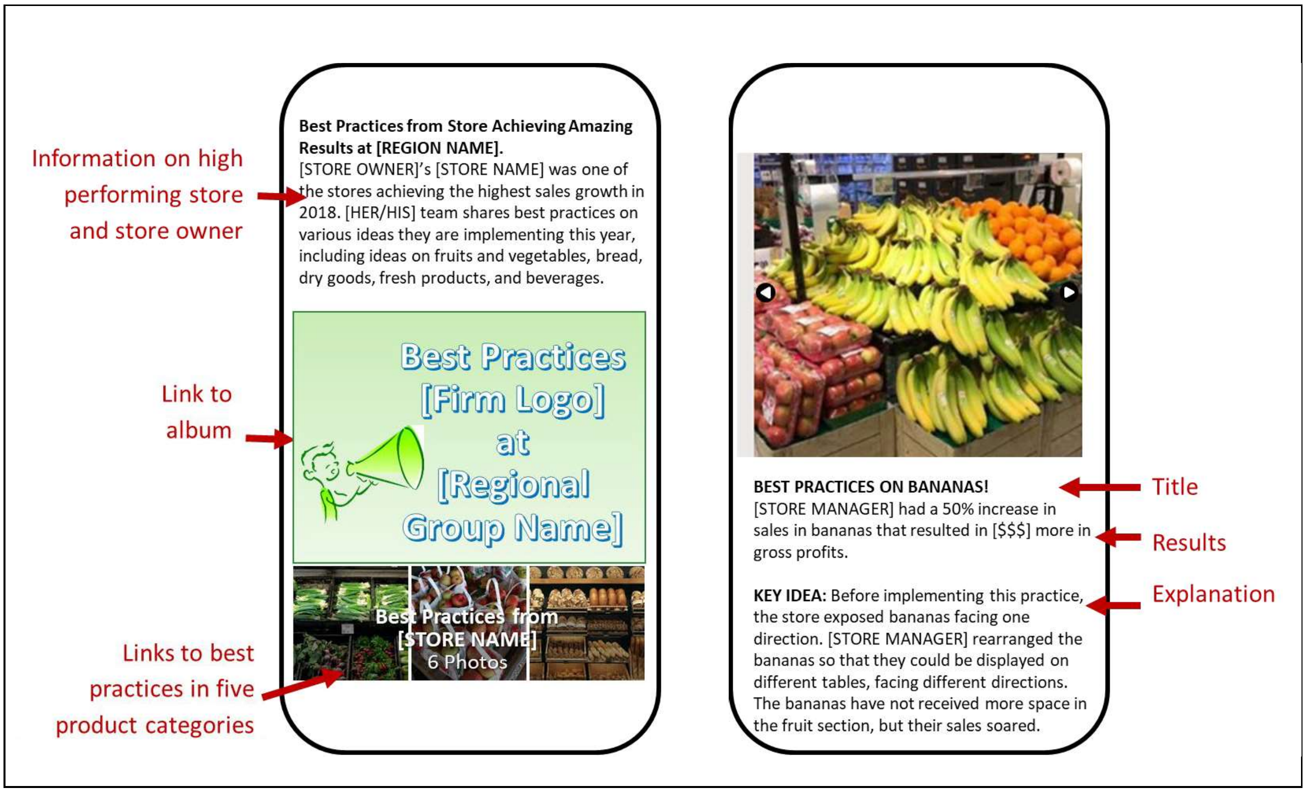
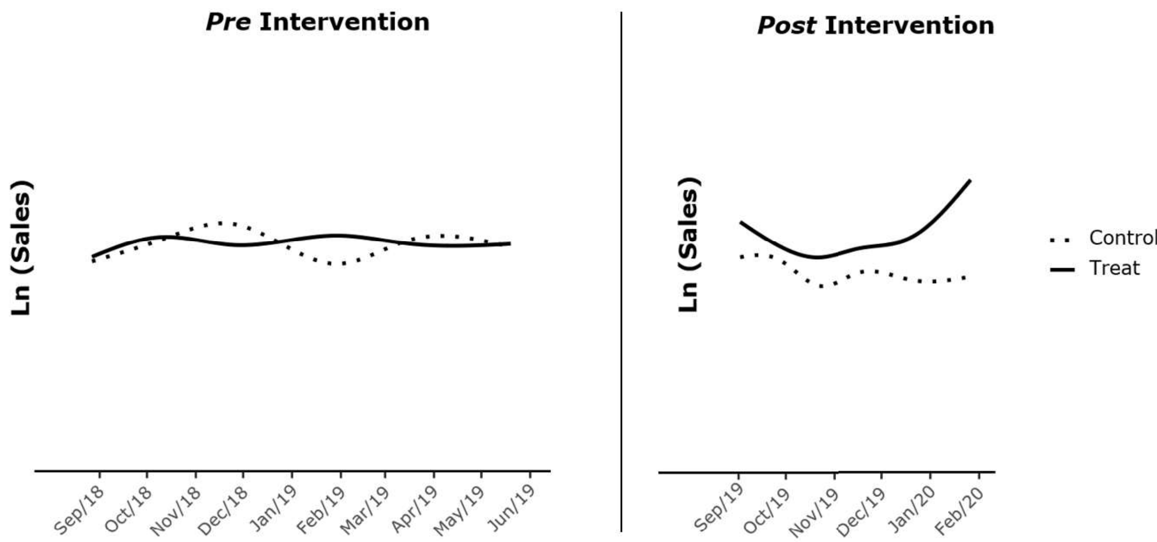


Figure 3: Visualization of Treatment Effects



The horizontal axis represents time (in weeks). Note that each month on this axis represents the end of the previous month (i.e. Feb/20 means January 31, 2020). The vertical axis is the residual of regressing *Ln(Sales)* on store fixed effects, week fixed effects, and store-time-trend fixed effects.

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
Low sales trends	Region 1	37	Region 2	53
Medium sales trends	Region 3	70	Region 5	51
	Region 4	55	Region 6	68
			Region 7	68
High sales trends	Region 8	57	Region 10	38
	Region 9	55	Region 11	35
	Total	274	*Total*	313

Panel B Covariate Balance between Treatment and Control Groups

	SSBP (treatment) group	**Control group**	**t-test p-value**
Varying by stores:	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	**0.05**
Average daily open hours	15.86	15.96	0.15
Weekly sales, August 2018 – July 2019 (US$)	101,235	103,560	**0.00**
Weekly sales trend, %	0.07	0.09	0.30
Population density (2018)	520.18	327.44	0.42
Average age (2018)	39.94	39.52	0.62
Average household size (2018)	2.15	2.22	0.36
Average household income (2017) (US$)	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
Varying by regions:	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

Variable	***Mean***	***Standard deviation***	***Minimum***	***Maximum***
Sales (US$)	98,020	41,392	1,062.241	319,316
System for Sharing 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
# Posts Made in the Regional Group	0.017	0.224	0.000	17.000
% of Posts Made in the Regional Group	0.304	3.570	0.000	88.889

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. *# (%) of Posts Made in the Regional Group* is the number (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 the number of observations for *# of Nearby Stores* is slightly lower (31,704), as we lacked location information for several stores.

Panel B Correlation Tables

Variable	1	2	3	4	5	6	7	8
1. Log_sales	1.000							
2. SSBP	**-0.016**	1.000						
3. Post	**-0.038**	-0.001	1.000					
4. Time	**-0.036**	-0.001	**0.866**	1.000				
5. Information Overload	**-0.067**	**-0.090**	0.003	0.003	1.000			
6. # of Nearby Stores	**0.149**	**0.241**	0.000	0.001	**-0.430**	1.000		
7. # Posts Made in the Regional Group	-0.009	**0.024**	**0.045**	**0.034**	**-0.020**	**-0.033**	1.000	
8. % of Posts Made in the Regional Group	-0.014	**0.026**	**0.046**	**0.035**	**-0.024**	**-0.042**	**0.777**	1.000

Notes: Correlations that are statistically significant at the 1% level are bolded. The number of observations is 31,759 (store-weeks), except the number of observations for *# of Nearby Stores* is slightly lower (31,704), as we lacked location information for several stores.

Table 3 Hypothesis 1: Does an SSBP Intervention on an ESN Improve Sales Trend?

	Dependent variable:
	Ln(Sales)
Post	-0.0270***
	(-7.22)
SSBP × Post	-0.0061
	(-1.05)
Post × Time	-0.0002
	(-0.60)
SSBP × Post × Time	0.0020***
	(4.15)
Adj R^2	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 region. *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***	-0.1010***	-0.0267***	-0.0419***
	(-7.99)	(-14.56)	(-7.13)	(-9.49)
SSBP × Post	-0.0027	0.0798***	-0.0027	0.0131**
	(-0.36)	(12.65)	(-0.36)	(1.96)
Post × Time	0.0002	-0.0089***	-0.0002	-0.0013***
	(0.80)	(-24.48)	(-0.51)	(-3.01)
SSBP × Post × Time	0.0017**	0.0097***	0.0017**	0.0029***
	(2.42)	(22.11)	(2.43)	(4.40)
SSBP × Moderator × Post			-0.0904***	-0.0281***
			(-23.92)	(-4.99)
SSBP × Post × Moderator × Time			0.0825***	0.0210***
			(8.51)	(3.05)
N	24,807	6,952	31,759	31,759
Adj. R^2	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 region. *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 Online Information Overload

	Dependent variable: Ln(Sales)			
	Less Information Overload	More Information Overload	Moderator: Information Overload_High	Moderator: Information Overload
Post	-0.0403***	-0.0176***	-0.0305***	-0.0268***
	(-5.50)	(-3.95)	(-4.03)	(-7.05)
SSBP × Post	0.0085	-0.0285***	0.0085	-0.0071
	(0.89)	(-3.62)	(0.89)	(-1.21)
Post × Time	0.0011*	-0.0005	0.0015***	-8.5E-05
	(1.95)	(-1.44)	(2.70)	(-0.29)
SSBP × Post × Time	0.0004	0.0027***	0.0004	0.0019***
	(0.55)	(3.07)	(0.54)	(3.82)
Post × Moderator			0.0049	-0.0019
			(0.56)	(-0.38)
SSBP × Post × Moderator			-0.0369***	-0.0065
			(-2.99)	(-1.05)
Post × Moderator × Time			-0.0023***	-0.0010***
			(-3.56)	(-2.88)
SSBP × Post × Moderator × Time			0.0024**	0.0010*
			(2.12)	(1.79)
N	14,387	17,372	31,759	31,759
Adj. R^2	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 region. *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 Offline 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***	-0.0325***	-0.0212***	-0.0283***
	(-4.15)	(-6.75)	(-4.02)	(-7.36)
SSBP × Post	-0.0109	0.0000	-0.0109	-0.0053
	(-1.30)	(0.00)	(-1.29)	(-0.90)
Post × Time	-0.0006	0.0004	-0.0017	0.0004
	(-1.40)	(1.08)	(-4.24)	(1.38)
SSBP × Post × Time	0.00301***	0.0007	0.0030***	0.0011**
	(4.84)	(0.96)	(4.86)	(2.24)
Post × Moderator			-0.0133*	-0.0054
			(-1.82)	(-0.91)
SSBP × Post × Moderator			0.0108	0.0069
			(0.94)	(0.99)
Post × Moderator × Time			0.0035***	0.0026***
			(6.69)	(5.46)
SSBP × Post × Moderator × Time			-0.0023**	-0.0012**
			(-2.42)	(-2.33)
N	17,925	13,779	31,704	31,704
Adj. R^2	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 region. *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: Does an SSBP Intervention Increase or Decrease Voluntary Inter-store Knowledge Sharing Outside the Formal Sharing Mechanism?

	Dependent variable: Posts Made in the Regional Groups	Dependent variable: % Posts Made in the Regional Groups
Post	-0.0086	-0.1780
	(-1.26)	(-1.11)
SSBP × Post	0.0602**	0.9240**
	(4.15)	(4.50)
N	31,759	31,759
Adj R^2	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 region. *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, the dependent variable measures the total number of posts made by employees in a store-week in their respective regional groups on the ESN. In Column 2, the dependent variable measures the percentage of posts made by employees in a store-week in their respective regional groups relative to the total number of posts made by these employees on the ESN.

Table 8 Panel A: 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***	-0.0282***	-0.0271***	-0.0270***
	(-7.23)	(-7.31)	(-7.23)	(-7.22)
SSBP × Post	-0.0027	-0.0099	-0.0026	-0.0056
	(-0.38)	(-1.27)	(-0.37)	(-0.50)
Post × Time	0.0006*	-0.0004	-0.0002	-0.0002
	(1.89)	(-1.45)	(-0.59)	(-0.59)
SSBP × Post × Time	0.0005	0.0038***	0.0005	-0.00139
	(0.87)	(5.44)	(0.88)	(-1.64)
SSBP × Moderator × Post			-0.0073	-0.0001
			(-0.81)	(-0.05)
SSBP × Post × Moderator × Time			0.0033***	0.0010***
			(4.35)	(5.65)
N	24,901	23,969	31,759	31,759
Adj. R^2	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 region. *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 8 Panel B: Moderating Effects of Knowledge Relevance

	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***	-0.0264***	-0.0270***	-0.0270***
	(-7.94)	(-6.64)	(-7.22)	(-7.23)
SSBP × Post	-0.0015	-0.0107	-0.0015	-0.0060
	(-0.20)	(-1.47)	(-0.20)	(-1.02)
Post × Time	-0.0001	0.0003	-0.0002	-0.0002
	(-0.45)	(1.01)	(-0.60)	(-0.59)
SSBP × Post × Time	0.0029***	0.0012**	0.0029***	0.0020***
	(4.11)	(2.22)	(4.12)	(4.27)
SSBP × Moderator × Post			-0.0092	0.0066
			(-1.03)	(1.45)
SSBP × Post × Moderator × Time			-0.0017**	-0.0020***
			(-2.15)	(-5.23)
N	24,418	24,452	31,759	31,759
Adj. R^2	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 region. *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.

Appendix 1: Examples of ESN Posts Prior to the 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 Best-practice Posts from the SSBP Intervention[33]

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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[33] With the exception of the picture in Figure 2 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.