The Effects of Digitally Delivered Nudges in a Corporate Wellness Program

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Abstract

We investigate how two digitally delivered nudges, namely light social support (non-verbal cues such as kudos or likes) and motivational messaging, affect employees' self-reported physical activity in an online, corporate wellness program. Within this unique field setting with data over several years, we find evidence that both types of nudges provide benefits beyond the effect of cash incentives. However, the effects vary by individuals, depending on whether the employee is active in exercising, and by time, depending on how long the employee has been in the wellness program. While light social support is found to be less effective over time, motivational messages are more effective with the duration in the program and generally more effective for inactive users. Our findings have implications for the design of wellness systems, suggesting different approaches depending on an employee's current activity level and tenure with the program.

Keywords: online health, digital nudges, online social support, motivational messages

Introduction

Many firms are interested in motivating their employees to increase their physical activity. The wellness benefits are numerous: employees with higher levels of physical activity are happier, more engaged at work, and take fewer sick days (Edries et al., 2013). Employees with higher levels of physical activity also incur lower costs for healthcare (Manning et al., 1991). Because of the importance of keeping employees healthy, more than 85% of large employers offer a wellness program (O'Boyle & Harter, 2016), targeting areas such as physical exercise, smoking, and weight loss (Mujtaba & Cavico, 2013b). A research report by Grand View Research estimates that the global corporate wellness market is expected to reach 97 billion US dollars by 2027 (MarketWatch.com, 2020). Most wellness programs rely on financial incentives such as insurance premium reduction and free gym membership to attract participation, spending between 50 to 150 US dollars per participant per year (Mujtaba & Cavico, 2013a). Still, participation in corporate wellness programs is low, with only 40% of U.S. employees who know of their company's wellness program participating (O'Boyle & Harter, 2016). Motivated by a lack of employee participation in corporate wellness programs, recent innovations nudge employees towards healthier behaviors using technology-enabled mechanisms such as mobile apps, self-monitoring, and online wellness communities (Liang et al., 2017; Salehan et al., 2017; Zhang & Lowry, 2015). The term "nudge" refers to any strategy of altering "people's behavior in a predictable way without forbidding any options or significantly changing their economic incentives" (Thaler & Sunstein, 2008, p.6). While there are positive reports on these technology-enabled wellness mechanisms, targeted research on specific nudge strategies and their long-term effectiveness is scant. Motivated by this gap, we study the effects of two specific digital nudging strategies—motivational messages and light social support—considering both their short- and long-term effects on physical activity in a real-world wellness program.

Motivational messages refer to electronic messages delivered to individuals to spur their desire and intention to engage in activities. In corporate wellness settings, these messages often consist of a variety of wellness-related information, tips, and quotes that are aimed to inspire positive wellness behaviors

(Rabin & Bock, 2011). An example of a motivational message is “According to WebMD, exercise increases your energy as well as serotonin levels in the brain, which leads to improved mental clarity.”

Light social support refers to “one-click” social messaging that one can send through online/mobile social platforms without providing any explicit written or verbal content. Examples of light social support include “like” on Facebook, and “heart” on Instagram and Twitter. Light social support is different from *substantive* social support, i.e., social support that comes with verbal or written content (Turner-McGrievy & Tate, 2013; Yan & Tan, 2014). The latter may be more informative for the recipient, but it is also less abundant being more costly for the sender in terms of time and effort.

Both motivational messages and light social support can be viewed as nudges. These interventions fall into Münscher, et al.’s (2016) taxonomy of nudges as filling a potential role in assisting, informing, and structuring decisions. In terms of the taxonomy, motivational messages can be viewed as a decision-assistance nudge, by serving as a reminder and facilitating employees’ commitment to wellness activities, and a decision-structure nudge, by providing information that connects wellness decisions to their benefits or costs. Light social support can play the role of a decision-structure nudge by changing the social consequence of a decision: it adds a social benefit of a “thumbs up” to a wellness activity. We target these two forms of digitally delivered nudges because both are popular and easy-to-implement; and, we have only a limited understanding of their effectiveness in wellness programs.

Specifically, beginning with text messages, although their use in health and wellness settings is not new (Grimstvedt et al., 2010; Mutsuddi & Connelly, 2012), previous studies generally have neither isolated the effects of motivational messages nor done so in field settings. Our study is distinguished from studies of textual messages embedded in interventions such as goal setting and shared message boards (Fjeldsoe et al., 2010; Fukuoka et al., 2010; Hurling et al., 2007; Lee et al., 2011) in that we isolate the effect of motivational messages separate from being a part of these broader interventions. The effect of motivational messages in real-life wellness programs warrants separate investigations for at least two reasons. First, employees who receive such messages may not have committed to wellness activities; it is an open question whether motivational messages would work in the absence of pre-commitment

(Prestwich et al., 2009). Second, most wellness programs in the field provide financial incentives for participation, which may undermine the effectiveness of motivational messages. The additional benefits of motivational messaging need to be studied within the context of these programs.

Similarly, many studies have highlighted the importance of social support in wellness contexts (Dadgar & Joshi, 2018; Treiber et al., 1991), but few have studied the nudging effect of receiving digitally delivered light social support in wellness programs. On the one hand, one may expect that receiving light social support can increase wellness behaviors because it adds additional social benefits to wellness activities. On the other hand, light social support, though being an external stimulus, only applies to employees who carry out wellness activities in the first place; such employees may be self-motivated and do not benefit much from light social support. In addition, light social support may suffer from additional limitations in corporate wellness settings: workplace social ties may be weak, and light social feedback may be drowned out by cash incentives in wellness programs. It is, therefore, necessary to investigate the effect of light social support in real-world corporate wellness programs.

Motivated by these gaps of understanding, our first research question is: *Do motivational messages and light social support lead to more physical activity among their recipients in a corporate wellness program?*

Another goal of this research is to examine how the effects of motivational messages and light social support evolve over an extended period. Given their light touch, a concern is that the effects of these nudges may disappear as their novelty fades. This is important since most wellness programs aim for long-term behavior changes; it is costly for companies to invest in wellness technologies that only last a short while. So far, the literature on motivational messages has been limited to short-term or one-time exposure (Cheung et al., 2008; Milne et al., 2002). Similarly, the literature on light social support has not tested how its effects change after a longer period of exposure. Our research attempts to fill these gaps by asking the second research question: *How do the effects of motivational messages and light social support change with a user's tenure with the wellness program*?

We draw upon self-determination theory (Ryan & Deci, 2000) and the transtheoretical model of health behavior change (Prochaska & Velicer, 1997) to develop research hypotheses about the short- and long-term effects of motivational messages and light social support on physical activity. Self-determination theory provides a high-level framework for understanding why individuals are motivated by external stimuli such as motivational messages and light social support to participate in physical activity, whereas the transtheoretical model lends insights on how the effect of these nudges can vary among different employees.

We test our hypotheses using three-and-quarter years' worth of data from an actual corporate wellness program that implements motivational messages and "kudos", a form of light social support, on top of weekly cash incentives. We estimate the effects of messages and light social support by applying a weekly panel with user fixed effects. To identify the effect of motivational messages, we leverage the fact that the delivery schedule of messages in our context is exogenously determined. In contrast, the number of kudos received is a function of employees' physical activity and thus may be partially endogenous; so, we conduct two additional sets of analyses. First, to alleviate the concern that the number of kudos received is endogenous, we use propensity score matching: We apply panel regressions on a dynamically matched sample, matching users that received kudos with those that did not but exhibited an equal propensity to do so. Second, we leverage the introduction of the kudos feature, an exogenous change during the study period, as a natural experiment to determine its impact on users' subsequent activity.

We find that both motivational messages and light social support are associated with subsequent increases in exercise frequencies among individuals exposed to them. These effects are however heterogenous. Motivational messages are most effective for inactive users, getting them to exercise. The effects of motivational messages increase in the users' tenure of platform use. In contrast, light social support becomes less effective as individuals' tenure of platform use increases. The differing dynamics, in the effectiveness of these two commonly implemented nudges in wellness platforms, offer insights for research and for platform and app designers, users, and implementors regarding the delivery of digital nudges for them to be most useful in spurring healthy behavior.

The rest of the paper is structured as follows: We first review relevant literature and develop the research hypotheses. We then describe our research design and results, followed by a discussion of findings and concluding remarks.

Related Work

Motivational Messages

Existing implementations of text messages can be divided into reminders and motivational messages that facilitate commitment (2016). Reminders notify recipients of predetermined activities to increase compliance, such as alerting a patient to take her medication at a particular time of the day. The reminders serve to follow-up on a planned behavioral intention (Prestwich et al., 2009). In contrast, motivational messages are not attached to a pre-existing intention; instead, they facilitate individuals to set or reinforce goals by offering, e.g., information on the benefits of physical activities, words of encouragement for people to take healthy actions, testimonies, and advice on physical activity (Buchholz et al., 2013).

Prior research on reminders primarily focuses on using a short message service (SMS) to remind one to comply with a planned goal-based activity (e.g., an exercise schedule, food, or medication intake). People receiving short messages outperform those who do not receive such messages in their physical activities, medication taking, and food care adherence (Haapala et al., 2009; Kim et al., 2006; Prestwich et al., 2010). Our study of motivational messages is distinguished from studies of reminder-based text messages (e.g., Calzolari & Nardotto, 2017). Reminders are useful when people have already planned for or predetermined a particular activity (Prestwich et al., 2009). However, in a field setting the messaging must operate in a more general fashion. Motivational messages are distinct in not being attached to an existing commitment to a specific activity (Milne et al., 2002; Prestwich et al., 2009).

Although studied, existing research on motivational messages is limited in two key ways. First, the research generally conflates the effects of motivational messages (e.g., sending messages about exercise benefits and behavioral and cognitive strategies to overcome barriers of behavior change) with other interventions such as goal setting and shared message boards (Fjeldsoe et al., 2010; Fukuoka et al., 2010; Hurling et al., 2007; Lee et al., 2011). This amalgamation of the various interventions makes it impossible to isolate the effects of the motivational messages alone on physical activities. Our field study, with messages delivered at an exogenous schedule, allows us to do so.

Another issue with studies of motivational messaging is highlighted by Milne et al. (2002), who supplied motivational messages using a standard health education leaflet. The effect of this one-time intervention was monitored over one week. More generally, prior studies predominantly examine the effect of motivational messaging on the initial activation of physical activities over a short period (15 weeks or less) (Cheung et al., 2008; Fjeldsoe et al., 2010; Fukuoka et al., 2010; Hurling et al., 2007; Lee et al., 2011; Wilbur et al., 2005). While the initial, short-term effect of messages has received academic attention, their impact over a sustained period is little understood. In comparison, our study is carried out over multiple years in an actual corporate wellness program. The longer time frame allows us to observe the ongoing effects of motivational messages in a field setting, beyond the positive effects that are due solely to the novelty of the messages or artificial experimental demands.

Social Support

Social support refers to information or actions resulting in an individual's perception of being "cared for and loved esteemed and valued [and] belongs to a network of communication and mutual obligation" (Cobb, 1976, p. 300). Social support can be delivered offline (including in-person) or online. Light social support is a simple form of online social support (Burke & Kraut, 2014; Eranti & Lonkila, 2015) expressed through digital gestures (e.g., "like", "upvote", "thumbs up") without verbal or written content (Wohn et al., 2016). A Facebook "like", for example, is "an easy way to let someone know that you enjoy [a post] and a way of giving positive feedback" (Facebook, 2018).

A large body of research has consistently demonstrated that offline social support has a positive impact on physical activities. For example, Treiber et al. (1991) showed that self-reported social support from family and friends positively correlated with physical activity among public school teachers. However, offline social support can be costly to provide and its availability is limited by its requirements of synchronicity and geographical proximity with those being supported (Scott, 1999). Online support can bypass these limitations by allowing the asynchronous delivery of support across distances.

A few studies show that online social support is effective for health-related improvements (see Rains et al. 2015 for a review). For example, Turner-McGrievy and Tate (2013) found that online social support, in the form of Twitter posts delivered by a weight-loss counselor and fellow participants, was related to weight loss. Yan and Tan (2014) found that both informational and emotional social support given and received in an online healthcare community helped patients move to a healthier state. However, online social support via verbal or written content requires considerable cognitive effort to compose; and thus, it is not provided as frequently as light social support. Light social support lets one send generic approval of the focal user's actions with less cognitive load and it is readily empowered by smartphone technologies where a rapid, single push can deliver acknowledgment and appreciation in real-time.

Prior research on the association between light social support (e.g., thumbs up) and recipients' perceived social support reveals mixed results. Compared to user-composed content (e.g., comments, posts, and messages), light social support is not associated with improvements in relationship strength, perceived social support, happiness, mood, loneliness, or tie strength between interactants (Burke & Kraut, 2013, 2014). However, Wohn et al. (2016) show that people do perceive light social support as social support. Similarly, in a controlled experiment, users receiving zero likes for a post show lesser belongingness and self-esteem needs being met compared to those receiving likes (Reich et al., 2018), supporting the potential value of providing light social support. These studies tie to the effects of light social support on attitudes but do not tie to observable behavior. Our setting investigates the use of light social support in a field setting, studying the effects on reported physical activity over an extended period. All these aspects distinguish our study from the previous literature, offering a clearer view of the potential impact of light social support.

Theoretical Background and Hypotheses

Self-Determination Theory and Wellness Behaviors

To understand how external stimuli such as motivational messages and light social support can affect physical activity, we first draw on self-determination theory (Ryan & Deci, 2000), a needs-based theory for explaining human motivation and behavior, including health behaviors such as adherence to exercise, weight loss, and medication adherence (Teixeira et al., 2012). Self-determination theory posits that human beings' innate needs for competence, autonomy, and relatedness can lead to *intrinsic motivation*, the state of being motivated to do a task for its inherent satisfaction. In contrast, people are *extrinsically motivated* when they do a task for separable values such as financial reward, status, praise, or social acceptance (Deci & Ryan, 1985). Multiple motivations can be at play and self-determination theory suggests that people's *internalization* of external regulatory states can vary, depending on the extent to which they perceive autonomy and an internal locus of causality. For example, if people do a task merely to satisfy external demands, obtain a financial reward, avoid punishment, or comply with social pressure, they are *externally regulated*. On the other hand, if they also view the task as congruent with their value or identity, they are in a state of *integrated regulation*. Greater internalization can lead to greater behavioral engagement, persistence, and personal well-being (Ryan & Deci, 2000; Teixeira et al., 2012). In the realm of health care, greater internalization has been associated with greater adherence to medications (Williams et al., 1998) and physical activity (Teixeira et al., 2012). Self-determination theory provides a useful theoretical foundation for studying motivational messages and light social support because in light of the theory, these digital nudges are supportive and non-controlling ways of promoting physical activity through the bolstering of internal motivations.

While self-determination theory underscores the importance of promoting self-determination in wellness behaviors, some strategies promote physical activity without addressing self-determination needs (such as tips and rewards). The theory is also silent on how a nudging strategy's effectiveness changes over time. That is where the transtheoretical model of change can fill the gaps.

Transtheoretical Model of Health Behavior Change

The transtheoretical model of change (Prochaska & Velicer, 1997) was originally developed to identify unique change stages and distinct change processes in smoking cessation. Its use broadened to studying other health behavior changes, including weight loss, medication adherence, changing diets, and HIV/AIDS prevention (Teixeira et al., 2012). Physical exercise is yet another setting that features long-running tasks with delayed benefits that is suitable for the transtheoretical model.

According to the transtheoretical model, successful health behavior changes progress through several stages, including contemplation, preparation, action, and maintenance (Prochaska & Velicer, 1997). *Contemplation* is a stage when people are considering a change soon, whereas *preparation* is in the immediate future. *Action* refers to a stage where people are changing to healthier behaviors, though still at a high risk of lapses. A *maintenance* stage is where people are at a lower risk of lapses and are working to prevent them. The transtheoretical model suggests that different stages are marked by different beliefs and require different self-change strategies (Prochaska & Velicer, 1997). For example, during the contemplation stage, useful change strategies include increasing awareness about causes and consequences of behaviors, assessing one's self-images with and without an unhealthy behavior, and assessing how a personal habit affects one's social environment. At the preparation stage, believing in one's ability to change becomes important, leading to the intention to act. Once people are in the action and maintenance stages, useful change strategies include getting social support, avoiding unhealthy cues, and providing rewards for positive behaviors. The transtheoretical model overlaps with self-determination theory in some recommendations (such as raising consciousness and self-image evaluation) but differs in others. For example, the transtheoretical model also advocates self-efficacy, social support, and task rewards. Moreover, the stage-dependent view of the model provides a rationale for contrasting the short- and long-term effects of digital nudges.

Applying the transtheoretical model in our context, we note that participants of corporate wellness programs could be in either contemplation, preparation, action, or maintenance stages, depending on whether they are still thinking about change or have already implemented changes to their exercise habits. Exactly pinpointing the change stages for each individual is challenging (West, 2005), but we can approximately infer change stages based on whether users are active in the program (i.e., have recorded physical activities). Those who have signed up for the program but have not recorded any activity on the site are deemed *inactive*. Because such users are interested in the program (as evidenced by the sign-up) but have not recorded activities, they are most likely in the contemplation or preparation stage. Those who have recorded physical activities are deemed as *active*. Active users have already acted on their intentions, and thus are more likely in the action or maintenance stage. This distinction between active and inactive users is further explored as we develop specific hypotheses using perspectives from both self-determination theory and the transtheoretical model.

Motivational Messages and Physical Activity

According to self-determination theory, individuals can better internalize a regulation if it provides a meaningful rationale for the task, conveys choices in a non-controlling manner, and encourages one's initiatives (Deci et al. 1994). Motivational messages as a form of suggestive but noncontrolling nudge can promote self-determined exercise behaviors. For example, motivational messages informing users about the benefits of physical activities ("Exercise lowers cortisol levels") can help users internalize the intrinsic value of the activities. Similarly, messages encouraging health initiatives ("Every journey begins with a single step") can promote users' sense of agency in starting new wellness initiatives, facilitating self-determination. Consistent with self-determination theory, the transtheoretical model endorses similar change strategies of raising awareness and promoting self-confidence. In addition, the transtheoretical model suggests that cues for positive behaviors are helpful (Prochaska & Velicer, 1997). Messages of encouragement and advice ("Scheduling a rotation of these activities is a workout plan that will work well for you.") can serve such purposes by cuing positive wellness activities. In sum, motivational messages can support self-determined physical activities and cue/reinforce positive changes as suggested by self-determination theory and the transtheoretical model. Therefore we hypothesize:

H1: *Activity frequency increases with the number of motivational messages received.*

Per the transtheoretical model (Prochaska & Velicer, 1997), individuals at differing stages of wellness-behavior change react differently to change interventions. Recall that employees who have not recorded any activity on the site are *inactive* and are more likely to be in one of the pre-action stages of contemplation or preparation. In contrast, employees who have recorded activity have acted on their intentions and thus are more likely to be in the action or maintenance stages. Tying this stage difference to the anticipated effects of motivational messages, we note that the benefits of motivational messages are to provide information on the value of physical activities, words of encouragement for people to take healthy actions, testimonies, and advice on physical activity (Buchholz et al., 2013). That is, motivational messages are hypothesized to operate as nudges that facilitate commitment (2016). As such, these messages are more relevant to inactive employees who are more likely in the contemplation and preparation stages. For employees who are at action and maintenance stages, instilling commitment is less essential. According to the transtheoretical model, for individuals in the action/maintenance stages, more relevant change strategies involve providing rewards/punishments, creating helping relationships, and stimulus control. These are beyond the scope of motivational messages. Therefore, active employees as a group are less likely to be influenced by the activation that messaging can support. The following hypothesis of a moderating influence is implied:

H2: *The effect of motivational messaging on activity frequency among active users is less than the effect among inactive ones.*

In addition to investigating the effect of messaging as a form of nudging intervention, there is a need to expand attention beyond the short-term effects of messaging on promoting activity. As users spend more time with the system, they receive more motivational messages. These motivational messages tend to center around a few related topics or themes (e.g., the health benefits of physical activities) but vary in the message content. This combination of topic coherence and content novelty supports cumulative benefits in the long run. Prior research in psychology shows that repeated exposure to a sequence of homogenous stimuli suffers from declining effectiveness, whereas repeated exposure to a sequence of heterogeneous stimuli does not and may see increasing effectiveness, especially when the stimuli are relatively complex and high in information content (Berlyne, 1970). In our context, the novelty of the messages' content can prevent a buildup of tedium and avoid declining message effectiveness. Furthermore, because each message adds novel information to a coherent theme, new motivational messages can build on and extend previous messages, enabling a cumulative effect that increases message effectiveness. Indeed, a study in the weight loss context shows that users find such varied messages to be useful and the users look forward to receiving them regularly (Shaw et al 2013).

Besides cumulative content, motivational messages can also benefit from cumulative trust in the messaging system, an important determinant of perceived technology value and use (Lankton et al., 2015). As users regularly receive novel and relevant motivational messages, they may find motivational messaging to be useful and trust it more. Such increased trust can lead to a strong motivational effect of messaging, as shown in other health contexts such as dietary choices (Tandon et al., 2020) and weight loss (Shaw et al., 2013). Given the coherence and novelty of motivational messages, each additional message is expected to provide cumulative utility and trust, thus we posit:

H3: *The effect of motivational messaging on activity frequency increases with the user's tenure with the program.*

Light Social Support and Physical Activity

Light social support, being without verbal or written content, can express a wide range of positive, affirmative emotions such as agreement, empathy, acceptance, or awareness (Hayes et al., 2016; Scissors et al., 2016). Drawing from self-determination theory, such social support can potentially provide extrinsic and intrinsic motivation for physical activity. First, a thumb-up from a colleague represents a form of social reward and approval, an external stimulus as identified by self-determination theory. When employees carry out physical activity merely to gain kudos, they are externally regulated. Second, receiving light social support can activate one's innate need for connectedness. By sharing physical activity and gaining the "likes" of friends, one can feel connected to these friends. Self-determination theory holds that relatedness can spur intrinsic motivation and behavioral engagement; in this case, engagement in physical activities (Ryan & Deci, 2000). Since one must register an activity to receive social support, the transtheoretical model provides additional backing for the positive effect of light social support: supportive relationships are one of the suitable change strategies for action and maintenance stages. Combining perspectives of self-determination theory and the transtheoretical model, we advance the following hypothesis:

H4: *Activity frequency increases with the amount of light social support received.*

Although both motivational messaging and light social support are external stimuli, there is an important difference: Because light social support is contingent on the posting of physical activities, employees must carry out the physical activities before social contacts can send light social support. This endogenous aspect has two implications. First, analyses of light social support must account for this endogeneity. Second, no counterpart of Hypothesis H2 (i.e., the contrast between active and inactive employees) applies to light social support – an inactive user cannot receive light social support.

Looking beyond the short-term effect and turning to our final hypothesis, we note that the reasoning behind the accumulating effects of motivational messages expressed as Hypothesis H3 does not apply to light social support. The cumulative content effect of motivational messaging hinges upon each motivational message being novel and high in informational content. This is not the case with light social support. As prior research in psychology has demonstrated, repetition of simple, homogenous stimuli is seen as redundant and declines in effectiveness (Berlyne, 1970). As users receive more of the same light social support with no new information, the tedium of repeated exposure is expected to accumulate and offset the positive benefits of light social support as summarized in Hypothesis H4. Similarly, the cumulative trust benefit of motivational messaging does not extend to light social support either. Unlike motivational messaging that originates from the system, light social support originates from one's social connections. The relevant trust for the latter is users' trust in their social connections, which exists outside of the system and is not likely to benefit from the minimal feedback provided by light social support on the platform. In sum, the cumulative benefits of motivational messaging do not carry over to light social support. Given the homogenous, low-information nature of light social support, additional light social support is expected to provide reduced benefits over time, leading us to posit:

H5: *The effect of light social support on activity frequency decreases with a user's tenure with the program.*

Methods

Research Context

The context of our study is a mid-sized health insurance firm in the midwestern United States. Starting from January 2014, the company began providing its employees with an innovative online wellness platform operated by a third-party vendor. The platform can be accessed through a mobile app or a browser on a computer. It is designed to motivate employees to engage in a wide range of physical activities that have wellness benefits, which include not only targeted exercises (e.g., running and gym workouts) but also activities that have wellness benefits as a byproduct (e.g., playing with children and shoveling snow).

The platform relies on employee self-reporting for activity logging. It allows an employee to report an activity up to a week after it takes place. The reporting tool has fields for activity type (chosen from an extensive list), date of activity, duration, and level of vigor (light, moderate, and vigorous) (see Figure B1 in Appendix B for the interface). The tool automatically estimates calories for the reported activity based on the activity type, duration, vigor, and MET (Metabolic Equivalent) values for different physical activities based on Ainsworth et al. (2011).[1]

As with many corporate wellness programs, the firm provides financial incentives for self-reported wellness activities. At the end of each week, the firm pays cash to users based on the number of reported physical activities in the past week: $2 for one activity, $4 for two activities, and $5 for three and more activities. The monthly amounts for such rewards are added to the paychecks of those eligible.

Besides the program's financial incentives, the wellness platform offers two forms of digitally delivered nudges. First, it sends motivational messages to users who register their mobile numbers with the platform via a short message service (SMS). The platform has developed an inventory of motivational messages with the help of psychologists, with a few of the messages being personalized based on users'

[1] See https://sites.google.com/site/compendiumofphysicalactivities/home for full details of individual activities. The MET is measured in kcal/kg/hour and is a ratio of the energy expenditure relative to the rate of expenditure at rest.

personality traits.[2] The personalized messages are often framed as being sent from the non-animated virtual coach *Kevin*. Table 1 provides a few examples of both kinds of messages sent to users. Only a small portion of the messages sent are personalized, and analyses did not indicate any difference in the effects of the two message types, so we collapse them during the analyses. All messages are sent at a pre-determined schedule: Their timing and content are not a function of user activities or outcomes. Therefore, motivational messages are purely exogenous to the exercising efforts of participants. Each user receives up to a few messages per week, without seeing the same message twice.

Insert Table 1 about here.

The platform also uses social networking to nudge users' wellness behaviors. A user can request to follow others from the company, called "friends." Once such a friend request is approved, the user can observe the friend's recent activities and comment on them. Starting on January 1, 2015, a new feature was introduced that allows users to send *kudos* to friends on specific reported activities (see a sample in Figure B2 in Appendix B). The user can send a Kudo to these friends by clicking on the "thumbs up"; a solid "thumb up" indicates a Kudo has been sent. These kudos are akin to "likes" on other web-based social media platforms. The user can additionally comment on friends' activities.

Participants

Our data cover a period from the program's inception in January 2014 to March 2017. In this study, we consider only users who reported at least two physical activities during their entire time on the platform, which reduces the number of users from about 1,200 to 467.[3] This dataset includes users who did not provide their mobile phone numbers (and thus did not receive any motivational messages) and those who did not add any friends (and thus did not receive any kudos). Eliminating such users would drastically reduce the sample size and representativeness. Instead, we keep such users in the main analysis and test the robustness of findings by excluding them at the end of the Results section. The demographics

[2] Such personalization is possible because the platform conducts a personality test when a user signs up.
[3] The company had about 1,200 employees that were all invited to sign up for the program, but some employees did not sign up. After the program's launch, the company continued to invite new hires to sign up for this program.

and other basic characteristics of our final subject pool are detailed in Table 2. Table 3 describes the key features of our study sample's weekly panel. All subjects were primarily residents of a large metropolitan area of a Midwestern city in the United States.

Insert Tables 2 and 3 about here

Model Specifications

The model specification here is for Model 4 in Table 4. The other models in Tables 4 and 5 are straightforward variations of this form:

$$Activ_{i,t} = \beta_1 Msgs_{i,t-1} + \beta_2 Kudos_{i,t-1} + \beta_3 logTenure_{i,t} + \beta_4 Kudos_{i,t-1} * logKudoWeeks_{i,t} + \beta_5 Msgs_{i,t-1} * logTenure_{i,t} + \beta_6 Cash_{i,t-1} + Week_t + \delta_i + \varepsilon_{i,t} \quad (1)$$

We model the activity frequency $Activ_{it}$ for user i in week t, as a function of digitally delivered nudges, including motivational messages and kudos. $Msgs_{i,t-1}$, the number of text messages received by user i in the week $t-1$, is included to capture any effect of message-based nudges.

To capture the effect of receiving a kudo, we include the number of kudos viewed by user i in the preceding week ($Kudos_{i,t-1}$). Because the reception of kudos is conditional on having been recently active, activity frequency may affect kudos received in the same week. Lagging alleviates the concern of reverse causality. We use the number of newly viewed kudos instead of the number of offered kudos because the former more accurately captures how users experience kudos. Specifically, if a kudo was offered a few weeks ago but a user only saw them in week t-1, we count it as "viewed" in week t-1. Conversely, if a kudo was offered in week t-1 but the user did not log in during that week, we do not count it as "viewed" in week t-1. This distinction between the support offered and that experienced has often been ignored by prior studies and potentially biased those results.

To model the natural life cycle of activity, and to account for the effectiveness of digitally delivered nudges over time (Hypothesis H3), we include the logarithm of user tenure $logTenure_{it} = \log(Tenure_{it} + 1)$ and its interaction with $Msgs_{i,t-1}$ in the model. Similar to prior work (Goes et al., 2016), we include the logarithm of tenure to capture the notion that the effect of time on user behaviors may decelerate as a user's time with the program increases. To explore the temporal moderation of the effect of Kudos, we generate a variable called $logKudoWeeks_{i,t} = \log\left(KudoWeeks_{i,t} + 1\right)$ which captures the logarithm of the number of weeks since user i could first receive kudos. We do this as the kudos feature was made available not from the very beginning of the platform but was introduced in the first week of 2015. If the user joined the platform before 1st January 2015, $KudoWeeks$ indicates weeks since this date, if the user joined after this date, it indicates their tenure on the platform. $logKudoWeeks_{i,t}$ was interacted with $Kudos_{i,t-1}$ to study the effect of receiving kudos over time (Hypothesis H5). The main effect of $logKudoWeeks$ is not included in Table 4, Model 4 as it is correlated with $logTenure_{i,t}$. Several control variables are included in the model. $Cash_{i,t-1}$, the cash reward given to user i for the activities reported in $t-1$, accounts for the effect of monetary incentives and is also a proxy for the previous week's activity. We lag cash incentives for the same reason as for lagging kudos. We include the week of the year fixed-effect $Week_t$ to account for seasonal variations that commonly influence outdoor physical activity (Uitenbroek, 1993). We also add individual fixed effects δ_i to capture the effect of time-invariant user attributes such as gender, occupation, location, physiology, exercise habits, reporting tendencies, and whether the user has registered to receive text messages.

Because our dependent variable $Activ_{i,t}$ is a count of physical activities, we estimate Equation (1) using a Poisson specification. We utilize Poisson over negative binomial given that the number of fixed effects in use would lead to incidental parameter problems for the negative binomial model. As a robustness check, we also use OLS and negative binomial specifications as alternatives and obtain similar findings (see the "Robustness Checks" subsection).

Results

Impact of Messaging on Activity Frequency

The results from Equation 1 and several variants are reported in Table 4 for the period January 2015 to March 2017, during which time the kudos and messaging features were active. In Model 1, we show the independent effects of kudos and messages. Models 2 and 3 test the effects of the interaction of each respectively with $logTenure$ and $logKudoWeeks$, respectively. In Model 4, corresponding to Equation (1), the effects of the two nudges are estimated jointly along with their interaction terms.

Insert Table 4 about here

Beginning with Hypothesis H1, the main effect of messages on employee activity, Model 1 in Table 4 does not indicate a significant effect. Further, when the interaction term is added to the model (Model 2), receiving a motivational message in the week prior has only a marginally significant effect of reduced activity among newcomers (i.e., *tenure* = 0) to the platform (i.e., $\beta_1 = -0.339, p = 0.081$). So, Hypothesis **H1** is not supported as a general tendency of messages influencing activity rates.

The effect of messages becomes clearer as we investigate Hypothesis H2, namely whether motivational messages have differential effects by the change "stages", as indicated by whether individuals were active in the past. We modify Equation (1) to include a binary indicator $PastActive_{i,t}$ which was set to 1 if the individual i had reported any activity between the weeks $(t-12)\ to\ (t-2)$. This variable distinguishes users who have any activity up to this time (*PastActive* = 1) from employees who are not active (*PastActive* = 0). Hypothesis H2 posits a higher effect of messaging for the inactive employees. We deliberately exclude activity in the week $(t-1)$ in defining this variable, as it would correlate perfectly with any cash or non-zero kudos received in the prior week. The moderation with tenure was also retained to ensure we distinguish the variance explained by individuals becoming active (changing their state) vs. just remaining on the platform long enough. Of particular interest for Hypothesis H2 is the interaction term (*Msgs* * *PastActive*). Model 4 in Table 4 is modified to add the main effect of the new variable and then the interaction; the results are presented in Table 5.

Insert Table 5 about here

As observed in Model 1 in Table 5 and consistent with the results in Table 4, the main effect of receiving messages again does not attain statistical significance as an overall main effect ($\beta_1 = -0.149, p = 0.115$). Hypothesis H1 is not supported. However, when the interaction term (*Msgs* * *PastActive*) is added to the model, a distinct pattern emerges. For the inactive employees (*PastActive* = 0), motivational messages had a positive effect on spurring exercise activity ($\beta_1 = 1.157, p < 0.001$). This effect is entirely counteracted among users who are active in the past, as indicated by the opposite and statistically significant interaction term ($\beta_7 = -1.317, p < 0.001$). The remaining terms in the model parallel the results observed with Model 4 in Table 4. As one would expect, we also observe that individuals who have been active in the past tend to be more likely to exercise in the subsequent weeks ($\beta_6 = 3.490, p < 0.001$). Thus, messaging does affect employees' activity, but not as a universal effect, supporting Hypothesis **H2** but not Hypothesis **H1**. Our results show that messaging has a positive impact on inactive users who are in the contemplation or preparation stage, motivating them to become active, and has less impact on active users who are more likely to be in the action or maintenance stage.

Hypothesis H3 concerns the longitudinal impact of messaging over the extended period of the study. Across all the models in Tables 4 and 5, we observe a statistically significant negative effect of tenure upon activity frequency (e.g., in Table 4, Model 4, $\beta_3 = -1.129$, $p < 0.001$). More significantly for our hypothesis, as seen in Table 4, the results indicate with marginal significance that the negative impact of messages attenuates over time (Model 4, $\beta_5 = 0.102$, $p = 0.061$). To get a sense of the interaction effect, the average marginal effects of receiving messages at different user tenure values are depicted in Figure 1. As seen in the figure, the effect of messaging increases and eventually becomes positive for users with over 25 weeks of tenure, lending marginal support for Hypothesis **H3**.

Insert Figure 1 about here

Impact of Light Social Support on Activity Frequency

Remaining with Table 4, we turn our attention to the analysis of light social support, identified as kudos, upon user activity. Beginning with the main effect, as observed in Model 4, holding tenure and $KudoWeeks$ at zero, kudos viewed in the previous week had a significant positive relationship with the activity frequency in the current week ($\beta_2 = 0.049, p < 0.001$). Thus, initially, the relationship between kudos and activity is positive, supporting Hypothesis **H4**.

However, this result must be interpreted in light of a statistically significant interaction effect, showing a diminishing relationship with the user's length of exposure to the kudos feature ($\beta_4 = -0.013, p < 0.001$), supporting Hypothesis **H5**. To illustrate the longitudinal pattern, we plot the average marginal effects of kudos over $KudoWeeks$ in Figure 2. The X-axis shows the weeks since the user was introduced to the Kudos feature (i.e., $KudoWeeks_{i,t}$) and the Y-axis shows the regression coefficient's magnitude. Initially, the relationship is significantly positive. For example, for a user who is new to Kudos (i.e., $KudoWeek$s = 0), the viewing of a recently received Kudo in the prior week would lead to a **5**% (= $e^{0.049}$-1) increase in the weekly activity frequency. The main effect of light social support at $KudoWeeks = 4$ (i.e., after the user has been exposed to Kudos for a month) is significantly positive ($\beta = 0.033, p < 0.001$). But, consistent with Hypothesis **H5**, the positive effects of light social support diminish over time and turn negative at about 10 months (i.e., $KudoWeeks = 40$) on average. After more than about 14 months (at $KudoWeeks = 56$), the effects become significantly negative.

Insert Figure 2 about here

Endogeneity of the Impact of Kudos

Kudos were sent by one's friends for activities logged by the focal user. Thus, the number of kudos received by a user has an endogenous component due to unobserved individual characteristics such as sociability (i.e., more sociable individuals are more likely to receive kudos), past behaviors (i.e., the more activities reported by the individual, the more kudos they may receive), and so on. To address these endogeneity concerns, we conducted two additional analyses. First, we apply a difference-in-difference analysis of the impact of the exogenous introduction of the kudos feature approximately midway through the study period. Second, we apply a matched-samples analysis to control for the endogenous component.

Introduction of the Kudos Feature

We utilize the introduction of the kudos features on January 1, 2015, as a one-time exogenous change to the platform. Before this date, users could follow friends' activities but could not send kudos to them. After this date, they could send kudos to friends based on their activities. Since users without friends could receive kudos neither before nor after the introduction of the kudos feature, we consider them as the baseline to compare to the behavior change of users that could receive kudos. A balance check between the two groups of users the week before the introduction of kudos suggests that they are not significantly different in major demographic and behavioral dimensions (Table A1 in Appendix A). The feature introduction is analyzed using a difference-in-differences approach. Users without friends comprise the control group and users with friends are the treatment group, with the introduction of kudos serving as the treatment. Figure 3 shows the mean activity frequency per individual within ±3 months of the introduction of the kudos feature. The dotted line shows the mean activity frequency of those users who had no friends on the platform before the kudos feature introduction. The solid line shows the results for those who had friends before the introduction of the kudos feature. Standard errors around the means are also shown. There was a general declining trend of activity in both treated and control groups into December 2015 which picked up for both at the beginning of the new year.[4] What is of interest is whether the uptick is greater for users with friends compared to those without, consistent with the hypothesized positive role of light social support.

Insert Figure 3 about here

To formally assess this, we create a panel consisting of user activities pre- and post-feature introduction. Only users active in both pre and post periods are included. We then model the number of total activities by user i in week t, $Activ_{i,t}$, as:

$$Activ_{i,t} = \beta_1 Post_t * HasFriends_i + \beta_2 LogTenure_{i,t} + \beta_3 Msgs_{i,t-1} + \beta_4 LogTenure_{i,t} * Msgs_{i,t-1} + \beta_3 Cash_{i,t-1} + WeekNo_t + \delta_i + \epsilon_{i,t} \quad (2)$$

As with Equation 1, Equation 2 was estimated as a Poisson regression to account for the count nature of the dependent variable. $Post_t$ is a binary indicator of whether the week was post (1) or pre (0) feature introduction. $HasFriends_i$ is a binary indicator of whether user i had friends (1) or did not (0). Because we

[4] The drop in overall activity at the end of the year is commonly observed in our data. This could be explained by the inclement weather in this midwestern city and/or holiday-related travels and activities. The increase at the start of the new year for both groups likely incorporates effects due to New Year's resolutions and the return to routines with the start of the year.

utilize a fixed-effects model, the main effects of $Post_t$ was absorbed by week number fixed effects ($WeekNo_t$) and that of $HasFriends_i$ by individual fixed effects (δ_i) and are not separately specified. To control for other determinants of activity frequency, in keeping with Equation 1, we also include the user's tenure at the week and the number of messages received the week before. The coefficient of the interaction $Post_i * HasFriends_i$ is our primary variable of interest, representing a difference-in-difference estimation of the treatment effect of introducing the kudos feature.

The other decision for the model is the selection of the window to use for the pre- and post-periods within the analysis. We let the window of observation vary from $\pm 1\ to \pm 6$ months around the feature introduction using Equation 2, as it is unclear how long the impact took to manifest. The results are shown in Table A2 in Appendix A with the estimated coefficient sizes for differing windows shown in Figure B3 in Appendix B. We report the 3-month results because 1-2 months may reflect a novelty effect and the estimate for the interaction term seems to stabilize after two months. Table 6 shows the results of the Poisson regression in Equation 2 using a 3-month window of observation.

Insert Table 6 about here

The interaction effect between having friends and having the kudo feature available was positive and significant (β_1 = 0.308, p = 0.03), suggesting that the introduction of kudos had a greater positive effect on activity frequency for those with friends, i.e., those who could benefit from the introduction of kudos, compared to those without friends, supporting Hypothesis H4 during the introductory period. This increase translated to a 23% increase in average weekly activity levels on average from their pre-feature selves for users with friends on the platform.

Matched Samples Based on the Propensity of Receiving Kudos

The difference-in-differences analysis focuses on the immediate effect of introducing the kudo feature, over several months. However, we are also interested in the longer-term effects of kudos upon physical activity. The analysis embodied by Equation 1 addresses the latter but suffers from potential endogeneity. The kudos received were not random; they potentially were affected by prior activities and personal characteristics of individuals such as sociability. To address these possible endogeneity issues, we employ a propensity-score matching (PSM) analysis (Dehejia & Wahba, 2002) as an additional robustness check on the possible effects of kudos upon activity.

Using PSM, we create a restricted panel in which users who did not receive kudos are predicted to have a similar propensity of receiving a kudo as those who did. To do so, we identify a subset of users within treated (received kudos) and control (did not receive kudos) conditions, such that the two groups of users are matched on the likelihood of receiving kudos ($GotKudo_{i,t}$). The matching is done by predicting the likelihood of user *i* getting any kudos in week *t* as a function of the user's number of friends $Friends_{i,t}$, last week's reported activity count $Activ_{i,t-1}$, last week's kudos sent count $KudoSent_{i,t-1}$, and the tenure on the platform $Tenure_{i,t}$. The logit regression to predict the propensity to get kudos is:

$$GotKudo_{i,t} = \gamma_1 Friends_{i,t} + \gamma_2 Activ_{i,t-1} + \gamma_3 KudoSent_{i,t-1} + \gamma_4 Tenure_{i,t} + \varepsilon_{i,t} \quad (3)$$

For each week, we generate a balanced matched sample with comparable likelihoods of receiving kudos. Figure 4 shows the distributions of predicted propensities of receiving a kudo in the final matched sample. The two distributions, for those who did and did not receive kudos are stacked on the graph for comparison. The figure shows that both treated (received kudos) and untreated users follow similar distributions of propensities, showcasing the relative balance in our matched sample.

Insert Figure 4 about here

The activity frequency of users in the matched sample is analyzed using Poisson regression analyses of the form in Equation 1. As the matching is done at a weekly level, a user is not necessarily included over multiple weeks in the PSM-matched data. This means that individual user fixed-effects cannot be estimated, month fixed effects however are retained. The results from our PSM analyses are shown in Table 7.

Insert Table 7 about here

Comparing the results from the PSM model (Table 7) and those from the Poisson fixed-effects model (Table 4), we note that the main effect of kudos (at *KudoWeeks* = 0) and the interaction between kudos and $logKudoWeeks_{i,t}$ retain their direction and statistical significance. Figure 5 (compared to Figure 2) indicates that the pattern over time is consistent with that of the full sample analysis, though the crossover point is slightly later with the matched sample analysis (at about 15 months vs. 10 months). Overall, the matched samples analysis supports the robustness of the findings with a very similar pattern of results, while suggesting a somewhat smaller initial effect size of kudos and a slower decay rate over time.

Insert Figure 5 about here

Robustness Checks

Alternative Regression Models

To ensure that our results are robust with our choice of the Poisson regression form, we also run the regressions in Equation 1 as OLS and Negative Binomial models, the latter to account for potential over-dispersion common in online activity frequency data. The results paralleling Model 4 in Table 4 are reported in Table A3 in Appendix A. The coefficients for both $Kudos$ and $Msgs$ are significant and consistent in magnitude and direction with our main results, as is their moderation by tenure.

Considering Self-Selection into Nudges

The delivery of the nudges we study, and their effectiveness, are contingent on users' self-selection into using features of the platform. Only users who explicitly added friends on the platform were eligible to receive kudos and only those who provided their mobile phone numbers received text messages. By considering those who did not register to receive text messages/kudos as equal to those who did register but did not receive nudges, we might bias our estimates of the effectiveness of nudges. To deal with this and as reported in Table A4 in Appendix A, we re-analyzed (based on Equation 1) the sub-populations of users who had registered their mobile phones with the platform (Models 1 and 2), had friends (Models 3 and 4) or registered mobile phones and had friends on the platform (Models 5 and 6). Table A4 shows the marginal impact of a kudo or a message by comparing, within a user, weeks where a nudge was delivered vs. those where one was not, conditional on registering to receive the nudge. The impacts of both messages and kudos were found to be consistent directionally and in terms of significance.

Discussion

We study a technology-enabled wellness program and its participants for three and a quarter years, observing their self-reported physical activity and how it is influenced by two digitally delivered nudges: motivational messages and light social support. Receiving motivational text messages has two interesting effects on physical activity. First, as predicted by the transtheoretical model of change, motivational messages are more effective among physically inactive employees than for active ones. Second, the effects of receiving motivational messages are initially negative, then increase and turn positive as users' tenure with the wellness program (and therefore exposure to motivational messaging) increases. In contrast, light social support in the form of kudos is effective in increasing weekly exercising when users are relatively new to the program. The effect diminishes with users' tenure with the program, however.

Implications for Research

Our research provides insights into the effects of two digitally delivered nudges on employee wellness behaviors in a real-world corporate setting. Overall, we find that motivational messages may not be immediately effective, but their benefits will manifest in the long run. To our knowledge, this dynamic effect of motivational messaging on health behavior has not been previously reported. Our findings are consistent with the cumulative content and cumulative trust benefits of motivational messaging, though more research is needed to determine the exact mechanism(s).

In contrast, light social support has immediate positive effects on physical activity, but such effects may not endure after repeated exposure. As discussed in the theoretical background section, because of the homogenous, low-information nature of light social support, repeated exposure can accelerate the onset of tedium and renders light social support less effective after the novelty wears off.

Our contrasting findings on the long-term effects of motivational messaging and light social support suggest, despite both being light-touch nudges, they influence behaviors in quite different ways and should be managed differently. These longitudinal effects were observable because of the relatively long-term nature of the field study. The results provide support for the value of looking beyond the immediate, one-time effects of situational interventions for promoting wellness, more generally.

Implications for Practice

Our findings contribute to the design and implementation of wellness programs, especially to the use of digitally delivered nudges, namely motivational messaging and light social support. Our findings can directly apply to similar corporate wellness platforms that combine monetary incentives and nudging technologies. Our findings suggest that different users may respond to different kinds of nudges. Motivational messaging is a promising approach for physically inactive users, though less so for active users. This suggests a promising strategy is to target motivational messages to individuals who are contemplating (but have not acted on) physical activity. We also find that motivational messaging requires repetition. Though users may not act on motivational messages initially, one should keep sending them because users show an increased tendency to act on such messages as their exposure to them increases.

In contrast, we observe a diminishing impact of light social support over time. To address this issue, one would require additional design considerations to maintain its initial effectiveness. For example, noting the lack of variation and information content may have contributed to light social support's diminishing impact, one may augment it by allowing supporters to add a short message or by introducing peer support forums, which allow the exchange of social support messages in addition to "thumbs-up."

More generally, our results offer promise for the use of digitally delivered nudges, in the form of motivational messaging and light social support, for promoting physical activity. Though most wellness programs provide financial incentives for users, many employees choose not to participate in wellness programs (O'Boyle & Harter, 2016). We observe that these nudges can operate alongside, and beyond, the effects of cash awards. Digitally delivered nudges such as kudos and motivational messages can operate at a marginal cost of effectively zero to the organization. Organizations and employees stand to benefit from adding such low-cost, effective digital nudges to wellness programs.

Limitations

Perhaps the most obvious challenge is the self-reported nature of outcomes, which is inevitable for wellness programs that track a large variety of wellness activities. One cause for concern is that the monetary incentives may cause over-reporting. However, the payment scheme was constant for all users in the study across time, and so is not expected to influence the main results. Also, such concerns may be partially alleviated by the prevalence of peer monitoring on the studied platform (via friend activity streams). Our user-fixed-effects specification also helps control for any time-persistent over-reporting. Still, future research should investigate potential misreporting with objectively measured wellness behaviors (such as those captured by activity trackers).

Another limitation of the present study lies in the potential endogeneity between the reception of light social support and activity, as both can be driven by the focal user's unobservable state. We alleviated some of these concerns by matching users who received kudos with those who did not but had the same probability of receiving kudos. We also used a natural experiment on the platform when the kudos feature was rolled out. Our results were robust to these alternative specifications, but further research is still warranted since we cannot fully control for the endogeneity within the field setting.

Lastly, our findings must be interpreted in a context in which a financial reward for activities is always present. We were unable to investigate how motivational messages and light social support interact with cash incentives. These are interesting directions for future research.

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Tables

Message Text	Message Type
According to WebMD, Exercise increases your energy as well as serotonin levels in the brain, which leads to improved mental clarity.	Non-Personalized
Fun Fact: On average, every minute you walk extends your life by one and a half to two minutes. Who ever said they don't have enough time to work out?	
Exercise boosts your metabolism. One pound of muscle burns 30-50 calories per day, while one pound of fat burns only 3 calories per day!	
Kevin: Being independent, observant, purposeful, you will find motivation by doing activities that excite you and using exercise as a means of escape.	Personalized
Tip: Resist the pressure to join large group exercises, you're better off getting outside and training for something that will challenge you.	
Kevin: Being competitive and goal oriented, think of exercise as training, or better yet, an opportunity for some friendly competition and to be your best.	

Table 1. Sample Text Messages Sent to Users

Statistics	N	Mean	St. Dev.	Min	Max
Subject Age (Years)	388	42	12.35	21	69
Subject Gender (1=Male)	414	0.77	0.42	0	1
Subject Weight (Pounds)	402	177.81	47.45	5[5]	365
Subject Height (Inches)	411	65.9	4.09	57	78
Number of Friends	467	1.46	4.29	0	38

Table 2. Sample Summary Statistics for 467 Subjects at the time of their registration

Variable	N	Mean	Std. Dev.	Min	Max
Weekly Activity Frequency (*Activ*)	41,128	1.38	2.51	0	25
Total Activity Duration in Minutes/Week*	12,156	217.31	147.19	20	1718
Weeks in the program (*Tenure*)	41,128	94.54	41.5	0	202
Weekly Kudos Received** (*Kudos*)	41,128	0.98	21.95	0	2688
Weekly Messages Received (*Msgs*)	41,128	0.01	0.15	0	3
Weekly Total Cash Rewards, USD (*Cash*)	41,128	0.09	0.64	0	5

*Duration is only observed for weeks where there was at least one activity. Some of the longest durations were due to, for example, employees spending time at a ski resort.
**Based on the time the user first saw the kudos, which could be more than a week ago.

Table 3. Weekly Summary Statistics of 467 Users between June 2014 and March 2017

[5] Two people listed their weight as 5 pounds; the next highest value is 97. Since weight did not impact any of the analyses in the paper, these participants were left in the dataset.

$DV = Activ_{i,t}$	(1)	(2)	(3)	(4)
$Msgs_{i,t-1}$	-0.015	-0.339^{+}		-0.330^{+}
	(0.062)	(0.194)		(0.193)
$Kudos_{i,t-1}$	-0.001^{**}		0.023^{***}	0.049^{***}
	(0.000)		(0.006)	(0.007)
$logTenure_{i,t}$	-1.135^{***}	-1.140^{***}		-1.129^{***}
	(0.067)	(0.067)		(0.066)
$logKudoWeeks_{i,t}$			-0.647^{***}	
			(0.022)	
$Kudos_{i,t-1} * logKudoWeeks_{i,t}$			-0.006^{***}	-0.013^{***}
			(0.002)	(0.002)
$Msgs_{i,t-1} * logTenure_{i,t}$		0.105^{+}		0.102^{+}
		(0.055)		(0.054)
$Cash_{i,t-1}$	-0.054^{***}	-0.055^{***}	-0.137^{***}	-0.062^{***}
	(0.010)	(0.010)	(0.010)	(0.010)
N	35,355	35,355	35,355	35,355
Users	467	467	467	467
User FEs	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes
pseudo R^2	0.301	0.301	0.297	0.303
AIC	123027.658	122987.143	123361.735	122679.585
BIC	123061.551	123021.036	123395.628	122730.424

Clustered standard errors in parentheses
$^{+}$ $p < 0.1$, ** $p < 0.01$, *** $p < 0.001$

Table 4. Effects of LSF(Kudos) and motivational text messages on weekly subsequent activity frequency.

$DV = Activ_{i,t}$	(1)	(2)
$Msgs_{i,t-1}$	-0.149	1.157***
	(0.118)	(0.187)
$Kudos_{i,t-1}$	0.033***	0.033***
	(0.005)	(0.005)
$logTenure_{i,t}$	-0.435***	-0.436***
	(0.042)	(0.042)
$Kudos_{i,t-1} * logKudoWeeks_{i,t}$	-0.009***	-0.009***
	(0.001)	(0.001)
$Msgs_{i,t-1} * logTenure_{i,t}$	0.050	0.050
	(0.032)	(0.031)
$PastActive_{i,t}$	3.466***	3.490***
	(0.137)	(0.138)
$Msgs_{i,t-1} * PastActive_{i,t}$		-1.317***
		(0.166)
$Cash_{i,t-1}$	-0.041***	-0.041***
	(0.009)	(0.009)
N	35,355	35,355
User FEs	Yes	Yes
Week FEs	Yes	Yes
AIC	100970.237	100852.923
BIC	101029.549	100920.709

Clustered standard errors in parentheses
*** $p < 0.001$

Table 5. Additional Analyses: Previous Activity

$DV = Activ_{i,t}$	
$Post_t * HasFriends_i$	0.308**
	(0.105)
$logTenure_{i,t}$	-0.168
	(0.157)
$Msgs_{i,t-1}$	-0.551
	(0.712)
$logTenure_{i,t} * Msgs_{i,t-1}$	0.234
	(0.209)
$Cash_{i,t-1}$	0.057***
	(0.013)
N	7,738
User FEs	Yes
WeekNo FEs	Yes
AIC	38014.476
BIC	38213.761

Table 6. Difference-in-Differences Test of the Impact of Introducing the Kudo Feature on Exercising (3-Month Window)

$DV = Activ_{i,t}$	(1)	(2)	(3)	(4)
$Msgs_{i,t-1}$	0.004	-4.994^{***}		-5.047^{***}
	(0.027)	(1.013)		(1.017)
$logTenure_{i,t}$	0.055^{**}	0.045^{*}		0.049^{*}
	(0.021)	(0.021)		(0.021)
$logKudoWeeks_{i,t}$	-0.000		0.030^{***}	0.028^{***}
	(0.000)		(0.002)	(0.002)
$Kudos_{i,t-1}$	0.059^{***}	0.059^{***}	0.060^{***}	0.048^{***}
	(0.008)	(0.008)	(0.009)	(0.008)
$Cash_{i,t-1}$		1.204^{***}		1.217^{***}
		(0.241)		(0.242)
$Msgs_{i,t-1} * logTenure_{i,t}$			0.055^{***}	
			(0.013)	
$Kudos_{i,t-1} * logKudoWeeks_{i,t}$			-0.007^{***}	-0.007^{***}
			(0.001)	(0.001)
N	4,981	4,981	4,981	4,981
Users	391	391	391	391
Week FEs	Yes	Yes	Yes	Yes
pseudo R^2	0.024	0.026	0.029	0.030
AIC	29566.926	29517.369	29425.160	29390.396
BIC	29931.675	29882.119	29789.909	29768.172

Standard errors in parentheses

$^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7. Impact of Kudos within Propensity Scored Matched (PSM) Sample.

Figures

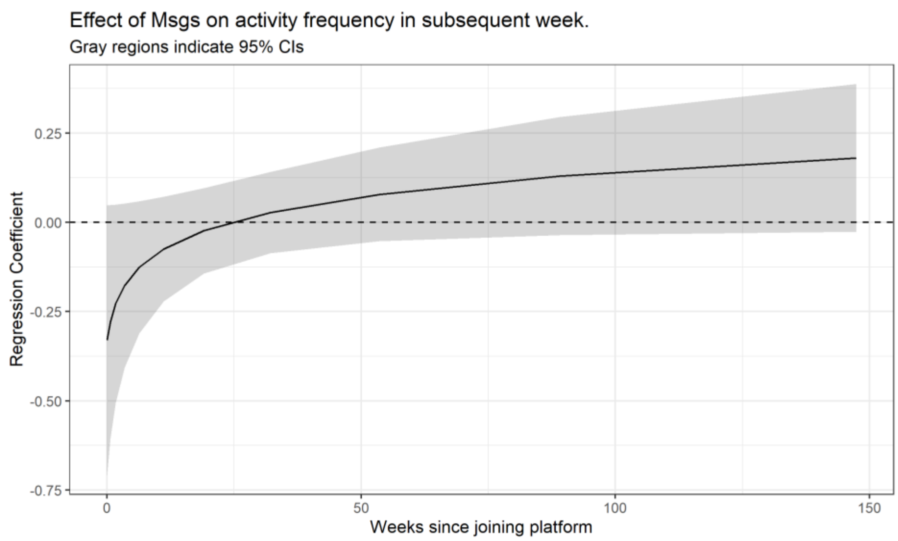

Figure 1. Tenure moderation of the impact of receiving any text message on weekly activity frequency.

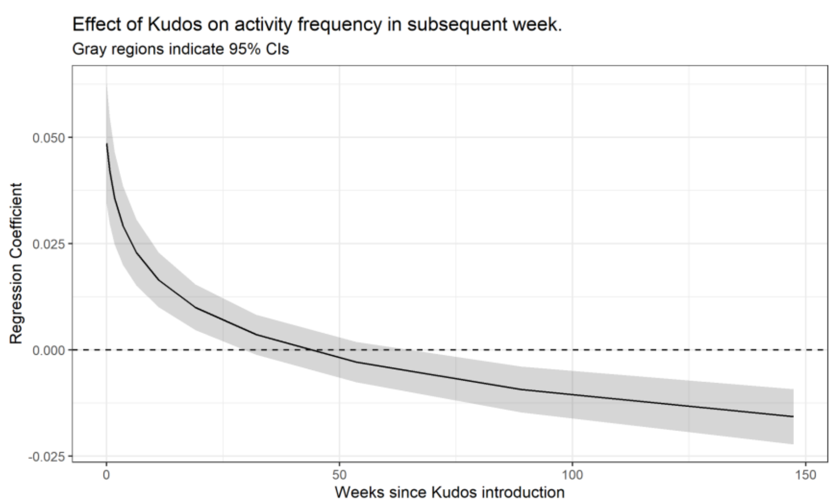

Figure 2. Tenure moderation of impact of Kudos on weekly activity frequency.

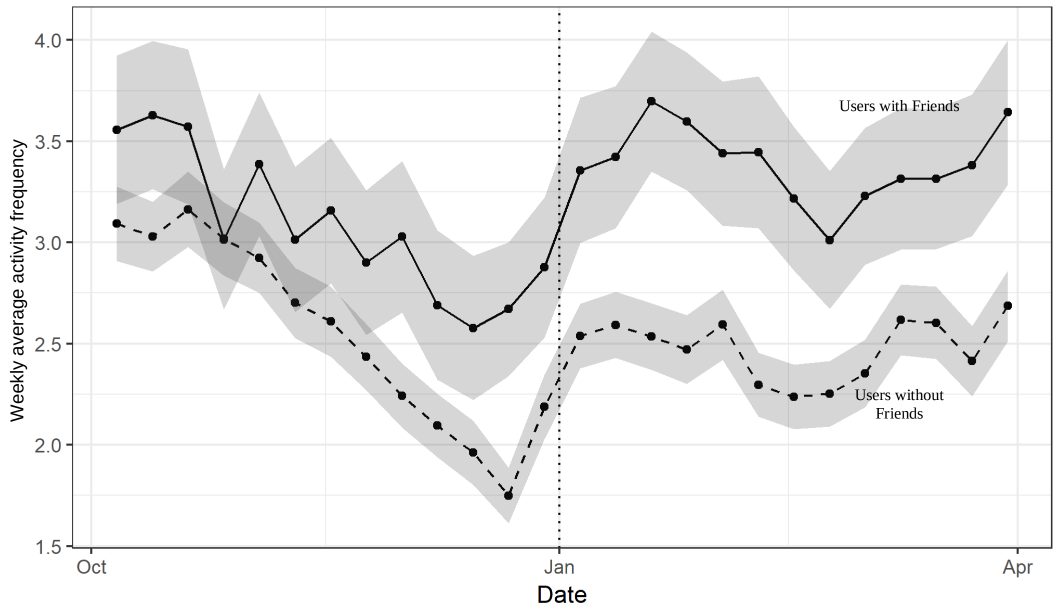

Figure 3. Per Individual Mean (and Standard Error) of Weekly Activity Frequency around the Introduction of the Kudo Feature at 1 January 2015.

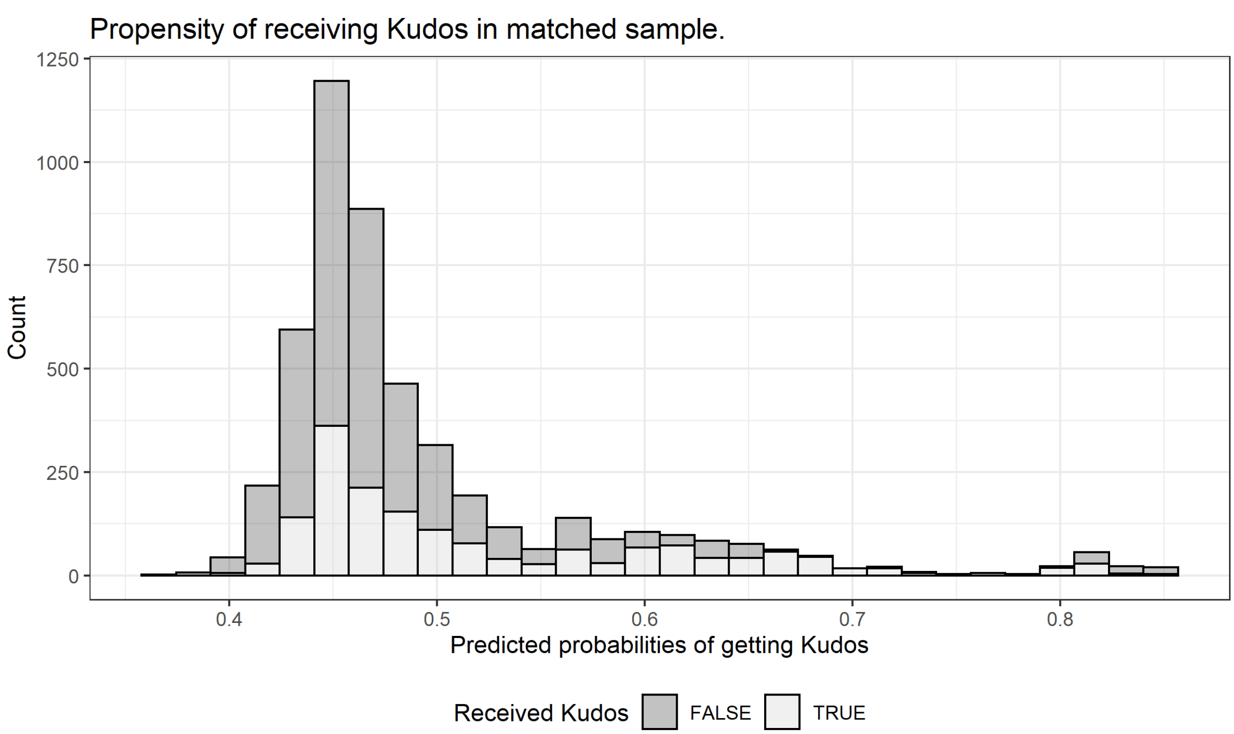

Figure 4. Superimposed Distributions of Predicted Propensity of Receiving Kudos across the Matched Sample.

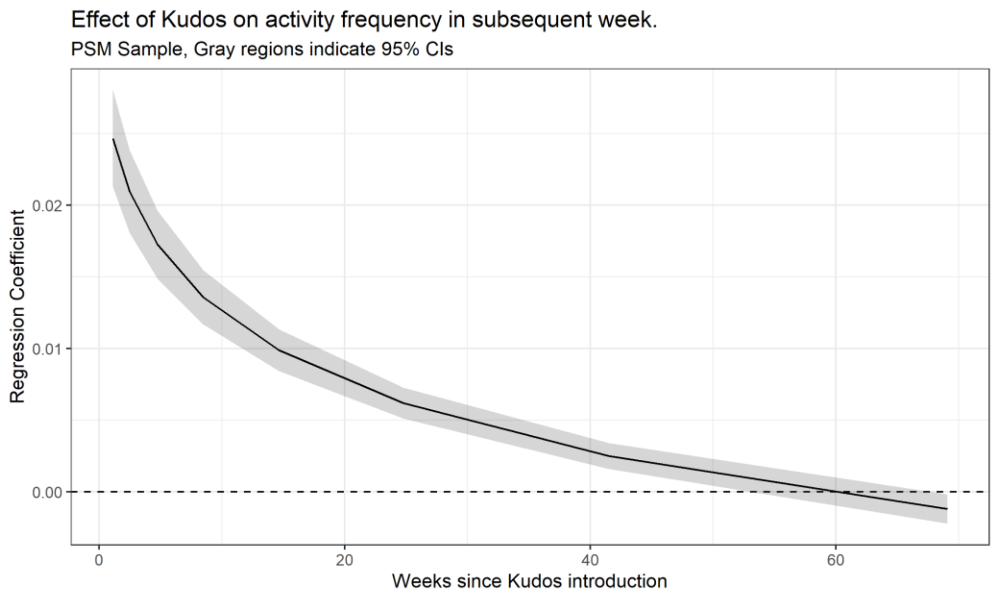

Figure 5. Impact of Kudos over time on subsequent weekly activity frequency (PSM sample)

Appendix A. Additional Tables and Figures

	Users without Friends		*Users with Friends*		
	Observations	Mean	Observations	Mean	P(diff != 0)
Age	258	41.96	68	41.55	0.800 (n.s.)
Sex (1 = Male)	277	0.77	72	0.82	0.328 (n.s.)
Weight	267	178	72	173	0.41 (n.s.)
Mean Duration	158	44.2	38	50.58	0.114 (n.s.)

Table A1. Balance Check for the DID analysis of Kudos Introduction

Window Size $DV = Activ_{i,t}$	1 Month	2 Months	3 Months	4 Months	5 Months	6 Months
$Constant$	2.746*	1.325**	0.923***	1.079***	0.984***	0.975***
	(1.097)	(0.416)	(0.273)	(0.207)	(0.164)	(0.144)
$Post_t * HasFriends_i$	0.063	0.063	0.116**	0.101**	0.075*	0.052+
	(0.076)	(0.052)	(0.044)	(0.037)	(0.033)	(0.030)
$logTenure_{i,t}$	-0.496+	-0.167	-0.084	-0.140**	-0.121**	-0.119***
	(0.289)	(0.108)	(0.069)	(0.051)	(0.038)	(0.032)
$Msgs_{i,t-1}$	-0.242	-0.065	-0.220	-0.042	0.238	0.300
	(0.416)	(0.341)	(0.308)	(0.321)	(0.276)	(0.244)
$logTenure_{i,t} * Msgs_{i,t-1}$	0.130	0.049	0.088	0.024	-0.060	-0.085
	(0.135)	(0.100)	(0.087)	(0.086)	(0.074)	(0.066)
$Cash_{i,t-1}$	-0.015+	0.018**	0.030***	0.037***	0.042***	0.041***
	(0.008)	(0.006)	(0.006)	(0.005)	(0.005)	(0.004)
N	2,093	4,807	7,738	10,753	13,805	16,985
User FEs	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes
AIC	8371.801	19318.809	31453.552	44069.919	56490.046	69261.309
BIC	8439.557	19448.365	31648.261	44332.105	56821.488	69663.794

Robust standard errors in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2. Impact of Kudo Availability on Monthly Activity Frequency.

$DV = Activ_{i,t}$	(1) OLS	(2) Negative Binomial
$Msgs_{i,t-1}$	-1.010***	-0.382***
	(0.265)	(0.079)
$logTenure_{i,t}$	-1.546***	-0.863***
	(0.114)	(0.013)
$Kudos_{i,t-1}$	0.280***	0.144***
	(0.075)	(0.024)
$Cash_{i,t-1}$	0.209***	0.065***
	(0.058)	(0.004)
$Msgs_{i,t-1} * logTenure_{i,t}$	-0.050***	-0.017***
	(0.014)	(0.001)
$Kudos_{i,t-1} * logKudoWeeks_{i,t}$	-0.017	0.020*
	(0.026)	(0.009)
N	41,094	35,355
Users	467	467
User FEs	Yes	Yes
Week FEs	Yes	Yes
AIC	172957.311	94246.626
BIC	173448.857	94738.071

Robust standard errors in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A3. Alternative specifications for the impact of Kudos and Msgs on subsequent activity frequency.

$DV = Activ_{i,t}$	(1) Mobile Registered Users Only	(2)	(3) Users with Friends Only	(4)	(5) Mobile Registered Users with Friends	(6)
$Msgs_{i,t-1}$	-0.018	-0.343+	-0.093	-0.972	-0.100	-1.035+
	(0.064)	(0.195)	(0.195)	(0.618)	(0.189)	(0.618)
$logTenure_{i,t}$	-1.144***	-1.143***	-1.848***	-1.816***	-1.712***	-1.691***
	(0.131)	(0.127)	(0.196)	(0.185)	(0.312)	(0.273)
$Kudos_{i,t-1}$	-0.002**	0.043***	-0.003**	0.025**	-0.005*	0.020+
	(0.001)	(0.007)	(0.001)	(0.009)	(0.002)	(0.012)
$Cash_{i,t-1}$	-0.007	-0.025	-0.099***	-0.109***	-0.062+	-0.082*
	(0.023)	(0.025)	(0.023)	(0.022)	(0.033)	(0.034)
$Msgs_{i,t-1} * logTenure_{i,t}$		0.106+		0.278+		0.297+
		(0.054)		(0.160)		(0.162)
$Kudos_{i,t-1} * logKudoWeeks_{i,t}$		-0.012***		-0.007**		-0.008+
		(0.002)		(0.002)		(0.004)
N	10,336	10,336	9,796	9,796	4659	4659
Users	133	133	115	115	91	91
User FEs	Yes	Yes	Yes	Yes	Yes	Yes
Week FEs	Yes	Yes	Yes	Yes	Yes	Yes
AIC	35021.998	34847.055	31529.671	31391.302	15043.501	14917.393
BIC	35050.972	34890.515	31558.430	31434.441	15069.288	14956.072

Robust standard errors in parentheses. $^{+}$ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A4. Robustness checks: sub-sample analyses of effects of Kudos and Text messages on activity frequency.

Appendix B. Additional Figures

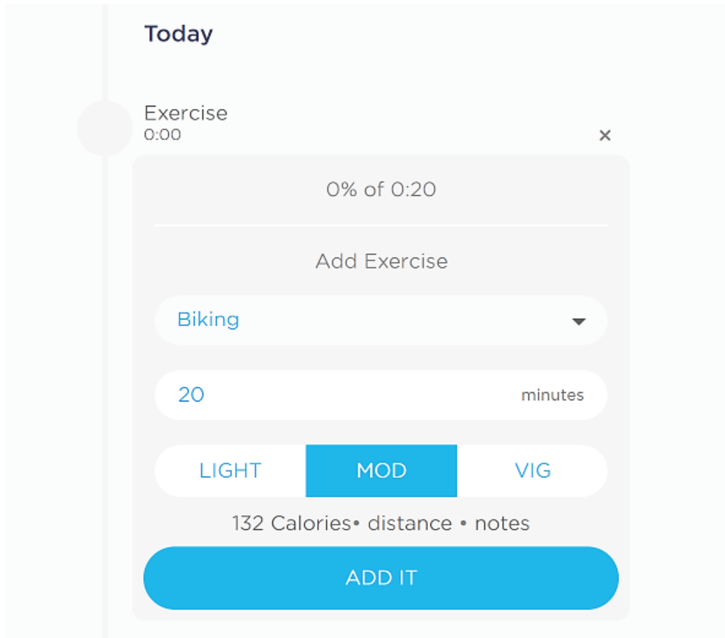

Figure B1. Activity Logging Interface

Figure B2. A User's Activity Feed Showing Friends' Activities (from John and Jane) and Kudos Sent

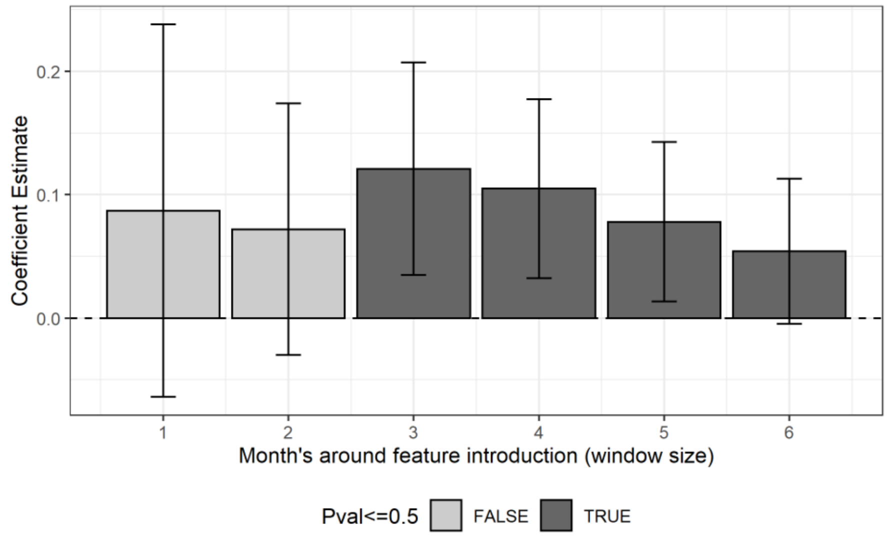

Figure B3. Estimate of Post-Kudo Introduction Difference-in-Differences (DID) over Window Size (months)