Planning and Performance: Experimental Evidence from Small Firms in E-Commerce*

Juan Pedro Ronconi†

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Abstract

This paper provides experimental evidence that behavioral frictions can affect operations planning in small firms, thereby reducing firm performance. I analyze a field experiment involving 14,500 e-commerce retailers in Argentina and Brazil conducted during the two weeks before Black Friday, a major sales event. The intervention randomized messages reminding managers that Black Friday was approaching and encouraging them to plan their pricing and advertising strategies. Treated firms shifted from generic to discount-related advertising and increased inventories before the event, but did not vary their pricing relative to the control group. As a result, sales increased by 5.2% for 60 days following the intervention. Machine learning methods reveal larger returns for relatively bigger firms with a stronger social media presence, suggesting strategic complementarities between firm size and light-touch interventions. These findings highlight that psychological constraints may be a meaningful barrier to the performance of small firms.

Keywords: business practices; planning; nudge; small firms; e-commerce

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†School of Business and Economics, Universidad de los Andes, Chile; jpronconi@uandes.cl

1 Introduction

Managers play a crucial role within firms—they plan, organize, and allocate resources to meet organizational objectives. Indeed, substantial evidence shows that managerial practices strongly affect firm productivity (Bloom and Van Reenen, 2007, 2010) and may explain up to 30% of cross-country variation in total factor productivity (Bloom, Sadun and Van Reenen, 2016). McKenzie and Woodruff (2017) further demonstrate that weak implementation of core business practices—such as marketing, record-keeping, and stock planning—constrains the productivity of small firms, which account for 70% of global employment (ILO, 2019).

What drives good practices in small firms? A body of work has examined business training and similar programs that address managers' and entrepreneurs' human capital constraints (McKenzie, 2021). In contrast, we know little about behavioral frictions in managerial decision-making. These frictions—such as inattention, memory constraints, or procrastination—can be especially consequential in small businesses, where key decisions often fall on a single individual who lacks the teams, systems, or external support available in larger companies. Recent survey evidence finds that owners and managers in small and medium-sized enterprises endorse the government's use of behavioral nudges, especially reminders (Tikotsky, Pe'er and Feldman, 2020).

This paper explores the potential of a light-touch behavioral intervention—nudging small firm managers to plan in advance for a major business opportunity—to improve operations planning and increase firm performance. I study a field experiment conducted in collaboration with a leading e-commerce infrastructure platform in Latin America (henceforth, the Platform), involving 14,494 small online retailers across Argentina and Brazil, two of the three largest economies in the region. During the two weeks leading up to Black Friday (BF) 2021, participating firms were randomly assigned to receive one of two types of messages sent by the Platform. The main message consisted of a brief reminder that BF was approaching, along with cues to plan pricing and advertising strategies for the event. This communication was designed to address managers' inattention and memory constraints. The second, exploratory message tested a longer version that additionally included a description of the loss-leader pricing strategy, a relatively uncommon approach among small firms like the ones in the sample. However, this communication failed to produce meaningful effects on pricing or performance, possibly due to cognitive overload leading to lower engagement.

The Platform provided rich data on sales, product listings, and firm characteristics, which I combine with web-scraped data on social media advertising to explore in detail the effects of the communications. I find that firms assigned to the nudge display 5.2% higher revenue during the 60 days since the start of the intervention. Interestingly, the strongest impact takes place during the week before Black Friday, where revenue goes up by roughly 10% compared to the control group, while on the day of the event there are only small and statistically insignificant differences across the two groups. I also find that the boost in sales is mainly driven by quantities, as units sold grew by similar amounts. These findings demonstrate that nudging managers to plan can be an effective way of promoting better firm performance, and suggest that behavioral constraints are a relevant friction around operations planning in small firms.

I analyze various mediating factors behind the increase in sales, finding robust evidence that the nudge successfully encouraged planning. Specifically, in the week preceding BF, prompted firms are more likely to advertise discounts on social media (15%), without increasing the total number of posts—that is, they tend to substitute generic advertising with discount-related content. Moreover, these firms also exhibit a 6% increase in the number of product variants listed as in stock (with no changes in the number of product categories), which is an unexpected finding given that the message did not mention inventory management (Altmann, Grunewald and Radbruch, 2024). Conversely, the intervention left prices unchanged. Using both full product listings and transaction-level data—including price cuts and non-price promotions, like quantity discounts—I find no evidence that treated firms priced differently from the control group. The absence of an effect indicates that managers are attentive to pricing, the most salient decision during a sales event like Black Friday. Behavioral constraints instead appear to operate on relatively less salient variables, such as advertising and inventory management.

Leveraging machine-learning techniques, I also explore how treatment effects vary across different types of firms. I employ all available covariates to estimate firm-level conditional average treatment effects (CATEs) with the generalized random forest method from Athey, Tibshirani and Wager (2019). The results indicate that the prompt is most effective for larger, more experienced firms with a stronger social-media footprint: Firms one standard deviation above the mean in terms of size record a 9.9% sales increase in the 60 days after the intervention. Yet, these firms do not expand advertising or inventory more than their smaller peers. The greater revenue gain therefore reflects a virtuous interaction between scale and the mediators—advertising and inventory planning—rather than a stronger direct effect on those channels. Very small enterprises may simply lack the scale or know-how to capitalize on light-touch interventions, making size itself a complement to the planning prompt among small firms.

This paper contributes to different strands of literature. First, it speaks to the growing evidence that business and managerial practices shape firm performance. (Bloom and Van Reenen, 2007; Bloom, Sadun and Van Reenen, 2012; McKenzie and Woodruff, 2017; McKenzie, 2021). This line of work has mainly focused on experimental work that tests for informational constraints in the adoption of better practices (Bloom et al., 2013; Bruhn, Karlan and Schoar, 2018; Anderson and McKenzie, 2022; Iacovone, Maloney and McKenzie, 2022) and has shown that information provision can work better when complemented with behavioral interventions (Lafortune, Riutort and Tessada, 2018; Dalton et al., 2021; Greiner et al., 2025). Recent evidence also suggests that light-touch interventions may be limited by more deeply ingrained mental models, which have been shown to lead to suboptimal managerial decisions around pricing (Han, Huffman and Liu, 2024). This study contributes with the insight that a low-cost, easily scalable behavioral treatment can improve operations planning and lead to better performance during a valuable period of time. It also informs the design and targeting of future programs by identifying which types of firms benefit the most from light-touch prompts that encourage better practices. Ultimately, managerial success may depend both on knowing what to do and on overcoming the small psychological frictions that get in the way of doing it.

Second, this project adds to the literature on planning and planning prompts, which has focused for the most part on household behavior. In an influential study, Milkman et al. (2011) show that adding a line in a mailed reminder asking recipients to write the specific date and time they would attend an on-site flu shot clinic raises vaccination rates by 4.2 percentage points over a 33% baseline. Abel et al. (2019) embed a structured implementation-intentions worksheet within a South African job-search workshop and find that, without lengthening search time, the exercise reallocates effort toward high-value activities, significantly lifting applications and job offers. My finding that prompted firms substitute generic with discount-related advertising, without increasing the number of posts, naturally complements their results from the firms side. Carrera et al. (2018) show that prompting gym members to schedule exact workout days and times fails to raise visit frequency, a null effect they argue underlines that planning improves performance mainly when execution windows are narrow or tasks infrequent, not for repeated behaviors like exercise. Consistent with this, my research shows that providing planning prompts two weeks before Black Friday—a once-a-year shopping event—yields positive effects. Working with firms, Robitaille, House and Mazar (2021) redesign delinquent corporate-tax letters into step-by-step “when-where-how” plans, which accelerates return filing by roughly four days and increases timely compliance by seven percentage points. In sum, my work complements these papers by providing experimental evidence from a large sample of firms that prompting owner-managers to plan their operations for a major business opportunity leads to better firm performance, especially among firms that have a relatively larger scale. Moreover, treated firms display enhanced operations in targeted and non-targeted behaviors, implying that plan-making may have positive spillovers on overlooked actions.

Finally, this research contributes to a growing body of papers studying "behavioral firms." This literature shows that firms may fail to maximize profits, both in developed DellaVigna and Gentzkow (2019) and developing countries (Hanna, Mullainathan and Schwartzstein, 2014; Kremer, Rao and Schilbach, 2019; Seither, 2021; Banerjee et al., 2023). In particular, Beaman, Magruder and Robinson (2014) find that micro-enterprises in Kenya forego up to 8% in profits for not keeping enough change—with the evidence being consistent with both inattention and present bias. Additionally, recent work by Gertler et al. (2025) show that various behavioral frictions—including distrust, present bias, and limited memory—can prevent small Mexican firms from accepting a cost-free service fee reduction, thus missing out on a profitable opportunity. I complement their work by providing evidence consistent with limited attention and memory constraints being important barriers to effective operations planning in advance of a major business opportunity. More in general, as Verhoogen (2021) points out, evidence of "behavioral firms" is scant beyond the agricultural sector, a gap that this paper helps to fill by focusing on small but relatively sophisticated firms that operate online businesses and by working with high quality data from a large sample of firms.

2 Context

E-commerce has globally become one of the most dynamic sectors, especially since the COVID-19 pandemic. In emerging economies it has been flagged as an opportunity for economic inclusion, innovation, and growth (World Bank, 2022, 2023). In this section, I describe the context of the experiment, focusing on characterizing the Platform and the importance of Black Friday as a business opportunity in the e-commerce sector and beyond.

2.1 The Platform

The experiment was conducted in advance of Black Friday 2021 in collaboration with one of the largest platforms for e-commerce infrastructure in Latin America. The Platform is a B2B company that provides web-hosting services for firms that wish to sell online, akin to Shopify. Crucially, it is not a marketplace—such as Amazon or Mercado Libre—as each firm owns an individual URL (*e.g.*, www.mystore.com). This has important implications for firm strategy and market dynamics, as firms must attract clients and gain reputation on their own, without a centralized system to facilitate that process (Tadelis, 2016; Cutolo and Kenney, 2021).

The Platform provides clients with templates to design their e-commerce website. Templates come already integrated with payment and delivery services. Social media pages and other tools for web analytics are easy to integrate. There is also a myriad of third-party apps available that can be integrated as well, ranging from accounting and inventory management software to chat bots and customer retention tools. In terms of pricing, they offer a menu of plans, each featuring a two-part tariff composed of a fixed monthly fee plus a variable rate on revenue ranging from 0.5% to 2%. In sum, the Platform provides access to an e-commerce ecosystem for a low entry cost, resulting in having a large client base mostly composed of small firms.

2.2 Black Friday

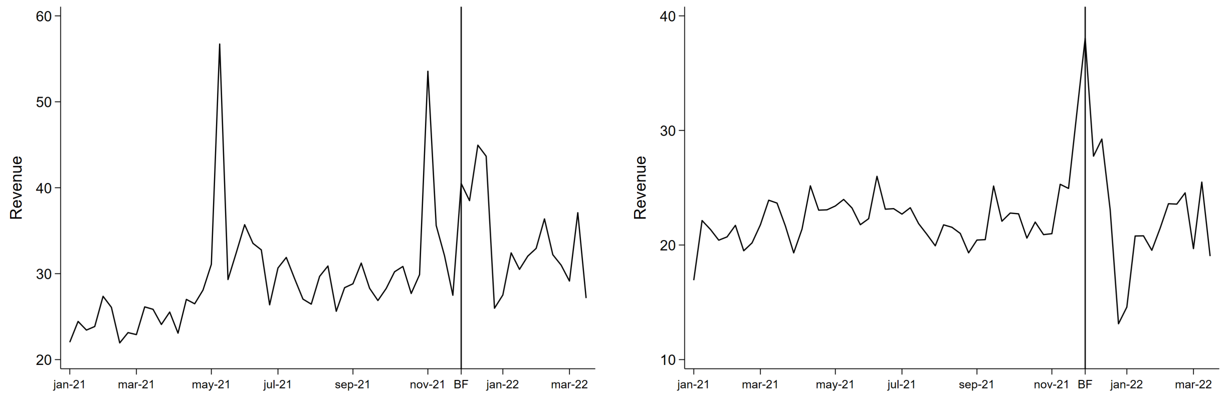
The experiment leverages Black Friday as an opportunity for online retailers to increase their sales and to expand their client base. The tradition of having large sales events on the Friday after Thanksgiving is said to have started in Philadelphia (US) in the 1960s, turning especially popular since the 2000s, partly thanks to the rise of e-commerce. In recent years, it became popular in Latin America and other parts of the world, too—for example, BF first occurred in Brazil in 2010 and in Argentina in 2013.

Black Friday is a massive sales event. According to Shopify, the largest web-host for online retailers around the world, during the 2022 event, 52 million consumers purchased from Shopify clients, spending a total of $ 7.5 billion (Shopify, 2022). In the sample of firms studied here, average sales per firm amounted to $ 58 on BF 2021, compared to a daily mean of $ 25 (+134%) between January 1, 2021 and March 15, 2022.

There are important institutional differences between Argentina and Brazil around Black Friday. While Brazil follows the US practice of combining Black Friday with Cyber Monday (another major sales event focused on e-commerce) around the same weekend, Argentina holds Cyber Monday about four weeks before Black Friday, making the latter a significantly smaller event for online retailers. This is observed in Figure 1, which plots the evolution of daily revenue by week among sampled firms, between January 2021 and March 2022. This important difference makes BF a significantly less salient event in Argentina than in Brazil, where it is the single most important sales event in the year.

Are Black Friday discounts “real”? That is, to what extent are prices actually reduced

Figure 1: Daily revenue by week



(a) Argentina **(b)** Brazil

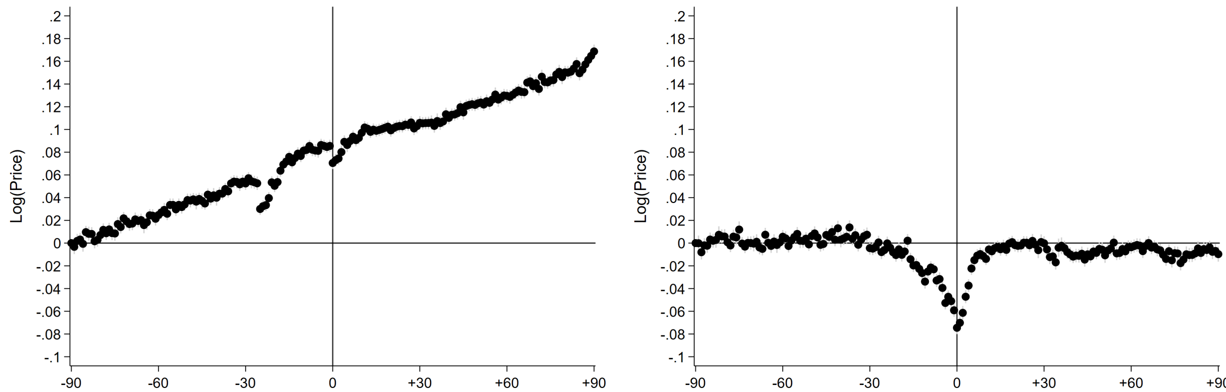
Note: The plots present the evolution of mean daily revenue in US dollars by week, among sampled firms in each country. The vertical lines indicate the week when Black Friday takes place.

compared to their pre-event levels? Figure 2 presents the daily price evolution of transacted product variants 90 days before and after BF, controlling for product variant fixed effects. Price reductions are, on average, small: roughly 1.5% in Argentina and 7% in Brazil. Note that these data cover all products, including those that were not offered at a discount. At the same time, there are no price increases during the few days before the event—a practice often denounced by customers.

Besides price discounts, firms may offer other promotions not captured in prices, such as quantity- or threshold-based discounts. Figure A1 in the Appendix shows the evolution of the daily share of firms that have transactions featuring non-price promotions, controlling for firm fixed effects (thus, coefficients represent differences with respect to the baseline period 90 days before the event). In Argentina, the mean share of firms offering non-price promotions is 6.6%, which goes up by roughly another 6 percentage points on Black Friday and by 12 percentage points around Cyber Monday. In Brazil, the full period mean is slightly larger, 7.5%, but it goes up by 13 percentage points on the day of Black Friday. Notably, the patterns observed in price and non-price promotions also reflect the higher importance that BF has in Brazil compared to Argentina.

Finally, Black Friday is also a major opportunity to attract customers and to potentially increase the client base. For example, user engagement on Instagram grows significantly during BF: the average number of likes on posts made that day is 109, compared to a mean of 89 (+22%) during the sampled period (see Section 3.1 for more details on the data).

Figure 2: Daily evolution of prices around Black Friday



(a) Argentina **(b)** Brazil

Note: Each plot presents event-study coefficients where the outcome variable is log-transformed transacted prices. Each coefficient corresponds to a day before/after Black Friday (period 0). The coefficient for period -90 is normalized to zero. The linear increase in prices in Argentina reflects the inflationary process taking place in the country at the time.

3 Methods

This section describes the data and sample analyzed in the paper, the design of the experiment, and the regression models to be estimated in the Results section.

3.1 Data and Sample

The Platform provided data on online operations and firm characteristics for the 14,494 stores in the sample. For each store we observe sales at both the product variant and firm levels from 1 January 2021 to 15 March 2022. The Platform records information at the product variant level (e.g., T-shirt style X in red) and also assigns a product category identifier so that all variants of T-shirt style X share the same product category ID. This structure allows prices to be analyzed at a highly disaggregated level while still enabling evaluation of effects at the product category level. Variant data include daily quantities sold and revenue, whereas firm-level data comprise daily revenue, discounts and shipping costs. Finally, the Platform extracted each store's complete listings—including list price, discounted price and available stock for each variant—on Black Friday and on the day before.

I also leverage data on social media activity, which provide a valuable window into the advertising strategy of firms. Specifically, I obtained all Instagram posts—including their date, caption, and number of likes—between November 1, 2021 and March 15, 2022. Importantly, Instagram is the most prevalent advertising channel for these firms (95% have an account).

The sample was selected on November 10, 2021, and consisted of the universe of firms operating in Argentina and Brazil that had not opted out of email/message distribution lists and that the Platform classified as "tiny" and "small" at the time. Specifically, the Platform classifies firms to be "tiny" if they had between 7 and 30 transactions in the last 90 days and "small" if they had between 31 and 150 in the same period. This resulted in a sample of 14,494 firms, with 7,676 from Argentina and 6,818 from Brazil.

Table A1 characterizes the sample. Firms tend to be young and small, with an average age of 23 months and sales of \$ 1,634 during the three months leading up to the intervention.[1] Moreover, 91% of the sample has at most 5 full time employees (microenterprises) and 50% has no brick-and-mortar stores (online only operations), although these metrics are self-reported and are available for 56% and 65% of the firms, respectively. Managers can also report the sector of the firm and 73% choose to do so. There is a high concentration in Clothing (51% of reporting firms), followed by Home & Garden and Health & Beauty, with 7% each, and Food & Drinks and Art & Antiques, with 4% each. The remaining sectors account for 27% of the reporting sample, including book stores, toy stores, and electronics, among other. Furthermore, managers tend to be sophisticated and to use tools consistent with skilled labor. For example, 95% of firms have an Instagram account, 72% have a Facebook account, and 40% have Google Analytics integrated to the store. Moreover, the typical manager integrates 4 apps to the online store and 4.43 on average, without counting Google Analytics.

Finally, the Platform shared information from a representative survey of clients conducted in late 2022, with more than 2,000 respondents in each country. The survey shows that in about 90% of cases, the person who receives communications from the Platform is the firm's owner. When it is not the owner, Platform officials report that the recipient is usually a close relative—*e.g.*, a tech-savvy son or daughter.[2] Moreover, women lead about two-thirds of the surveyed enterprises, underscoring the potential of e-commerce to foster female entrepreneurship (Alhorr, 2024).

[1] For reference, the monthly federal minimum wage was around \$ 200 in Brazil and \$ 160 in Argentina during this period.

[2] Because the Platform does not systematically record this information, I cannot identify the role of the person receiving the messages in each firm. Accordingly, I use "manager" as a generic label—referring mainly to owner-managers—throughout the paper.

3.2 Experimental Design and Implementation

The experiment consisted in the distribution of messages to the managers of the 14,494 online stores in the sample. Firms were randomly split into three groups: the main treatment, involving a nudge (T1); a second, exploratory treatment, that combined the nudge with an explanation of a pricing strategy—the loss-leader approach (T2); and a pure control group (C). The nudge involved the following message:

> ***Black Friday*** *is just around the corner! Take advantage of this event to increase your sales and participate in a raffle to win one of three iPads. If you want to participate, read the following message carefully.*
>
> *Black Friday (Nov-26) is a* ***great opportunity*** *to increase sales by offering discounts and promotions for a short period of time.* ***Have you already planned yours?***
>
> *At the same time, don't forget to* ***communicate*** *your discounts and promotions on* ***social media****. You can offer great things, but if your audience doesn't know about them, they won't have any impact, so don't miss the opportunity!*
>
> *To participate in the raffle for one of three iPads, just send the flyer you will use to promote your main Black Friday discount. You have time until Nov-25!*

The message is designed to prompt managers to plan their pricing and advertising strategies for BF. It includes a reminder that the event is approaching and a raffle to increase the salience of the message. Importantly, the raffle didn't alter managers' incentives significantly, evidenced by a negligible participation rate: only 98 managers submitted their flyer (2.03% of firms in T1). The message also uses language that creates a sense of urgency and importance about the event: "*Black Friday is just around the corner!*;" "*a great opportunity to increase sales*;" "*don't miss the opportunity!*" These features, including the explicit planning prompt, help to alleviate attentional and memory constraints in relation to pricing and advertising (Beshears, Milkman and Schwartzstein, 2016).

An alternative interpretation is that the message is actually providing information, as opposed to addressing behavioral constraints, for example by informing managers about the existence of Black Friday or of its importance. There are various reasons to think this is not the case. For example, Section 4.2.2 provides evidence that the intervention did not affect participation in the event, making it implausible that managers were unaware of its existence (if they had been, the message should have increased participation on the margin). Additionally, Section 4.3 shows that effects were stronger among older stores, more likely to have been active for over a year—that is, stores that had experienced Black Friday before, and thus are more acquainted with the magnitude of the event.

The second treatment aimed to provide store managers with a novel pricing idea for the event—an aspect of operations they often find particularly challenging. Specifically, it offered an introduction to the loss-leader pricing strategy, a more sophisticated alternative to flat discounts and therefore potentially valuable to managers. The full text of the message appears in Appendix Section A.2.1. According to Platform officials, managers typically rely on simple pricing heuristics, such as variable costs plus a perceived reasonable mark-up. This pattern aligns with evidence from McKenzie and Woodruff (2017), who document poor marketing practices among small firms in Mexico and Chile: only 24% and 44% had visited at least one competitor to check prices in the previous three months. Despite its potential, T2 did not affect firm performance, as discussed in Section 4.4.

The timeline of the interventions was as follows: After collecting baseline data on November 10, the sample was stratified and firms were randomly assigned to one of the three groups. Stratification was made on firm characteristics, including revenue (above or below median), country, sector, firm age, and sophistication (an indicator for the firm using Google Analytics or having more than 7 apps integrated to the store, which represents being in the top 10% of the distribution of integrated apps). There are 112 strata.

Managers were assigned to receiving the same message twice: The first round was distributed via email on November 12, exactly two weeks before BF. The second round was distributed on November 17, via an in-platform message, which consists of a small window that pops up when the manager logs into the online store. All communications were distributed by the Platform, who regularly sends messages through these channels. Open rates were 33% for the first round (email) and 71% for the second round (in-platform). Overall, 82% of treated managers read at least one message and 22% read both of them.

During the second communication round, a protocol deviation affected Argentine firms: those assigned to T1 received both messages simultaneously, while those assigned to T2 received none. Although this can pose a threat to the estimation of treatment effects, because T2 ultimately had no meaningful impact on revenue, any attentional crowding-out of the first message would bias the estimated effect of the nudge downward among Argentine firms. Moreover, reassuringly, since the Brazilian sample was unaffected, I replicate the main analysis and find qualitatively similar results using only Brazilian firms (Table A5 in the Appendix).

3.3 Empirical Approach

Throughout the paper I estimate three types of models, depending on the nature of the data and the desired type of estimation. In all cases I focus on intent-to-treat (ITT) effects, relying on treatment assignment as a source of identification. The main specification when panel data are available is as follows:

$$Y_{i1} = \beta T_i + \gamma Y_{i0} + \delta_{s(i)} + \epsilon_i \tag{1}$$

Where Y_{i1} in an outcome of interest for firm i in the post-treatment period and T_i is an indicator for being in the treatment group. I follow McKenzie (2012) and include Y_{i0}, the pre-treatment value of the outcome of interest, to improve precision. Finally, $\delta_{s(i)}$ is a vector of strata fixed effects (Bruhn and McKenzie, 2009). Standard errors are heteroskedasticity-robust under the baseline specification. For robustness, I also provide randomization inference (RI) p-values based on 10,000 permutations, following the recommendations in Abadie et al. (2020), which argues that RI p-values are a more appropriate measure of significance in the context of randomized controlled trials (where uncertainty comes from treatment assignment and not from sampling).[3]

To obtain dynamic treatment effects, I estimate event study models of the following form.

$$Y_{it} = \alpha_i + \gamma_t + \sum_{m=-G}^{M} \beta_m T_{i,t-m} + \epsilon_{it} \tag{2}$$

Where Y_{it} is an outcome of interest for firm i in period t, α_i is a firm fixed effect, and γ_t is a time period fixed effect. The regressors of interest, $T_{i,t-m}$, are indicator variables taking value 1 when firm i was assigned to the treatment group m periods before t. Note that all firms were assigned to the treatment group on the same period, implying there is no staggered roll out of the intervention, so the recent developments in the literature do not apply to this case (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021). The vector β captures the dynamic treatment effects with respect to a baseline period, which I set to be the one right before the onset of the experiment. Standard errors are clustered at the firm level under this model.

[3]Note that standard errors should not be clustered because treatment was assigned at the firm level and there is one observation per firm under this model.

Finally, when only cross-sectional data are available, I estimate the following model.

$$Y_i = \alpha + \beta T_i + \delta_{s(i)} + \epsilon_i \tag{3}$$

Where T_i is an indicator for being assigned to treatment and $\delta_{s(i)}$ is a vector of strata fixed effects (Bruhn and McKenzie, 2009). As in the first approach, standard errors are heteroskedasticity-robust.

Table A2 presents a check that randomization was successful. I regress the treatment group indicators on baseline characteristics, testing whether the latter have predictive power over the former. Reassuringly, individual characteristics are not significant predictors and F tests of joint significance fail to reject the null. Baseline characteristics include revenue between August and October 2021; months since entry; indicators for the different possible numbers of employees, the different possible number of brick-and-mortar stores, and the different possible sectors (non-reporters are the omitted categories in each case); indicators for having Instagram and Facebook pages linked to the online store; indicators for having integrated Google Analytics; number of integrated apps; and country.

4 Results

Equipped with the identification strategy laid out above, and having checked that treatment and control groups are balanced, this section presents the paper's findings. First, I show that planning increased revenue for treated firms. Second, I turn to mechanisms, providing evidence that the nudge successfully led managers to plan in advance for the event, affecting both targeted and non-targeted behaviors. In particular, although the messages did not alter pricing decisions, they did lead to more effective advertising and inventory management. Third, by applying machine-learning techniques, I uncover meaningful heterogeneities in the nudge's treatment effects, enriching our understanding of the conditions under which nudges work on firms. Finally, I analyze the alternative message, demonstrating that it had no impact on revenue and offering suggestive evidence on why it failed to do so.

4.1 Main Effects on Revenue

In this section I present the baseline results from the paper: the effect of the nudge on online-stores' revenue. I leverage the randomization of messages described in Section 3 as a source of exogenous variation on being nudged to plan operations for Black Friday. Since the messages only involve a light-touch planning prompt, they would only affect behavior and performance if managers are constrained by psychological factors such as inattention and imperfect memory. Indeed, findings indicate that treated firms outperform their peers in the control group.

Table 1 reports ITT estimates based on Equation 1, comparing firms that received the nudge to those in the control group. Columns 1 and 2 show the effects during the first and second week after the start of the experiment (the pre-Black Friday period). We see an immediate increase in sales in Week 1, although noisily estimated, at roughly \$ 1.11 per day (4.7% relative to the control group). In Week 2, when both message rounds had been distributed, the advantage for treated firms grows to \$ 2.27 per day (9.9%). This is the peak of the effect throughout the sample period. Notably, this advantage vanishes on Black Friday itself, implying that the surge in demand allows control firms to catch up, erasing the gains from advance planning. However, in the 45 days after BF the benefit for treated firms re-emerges, at \$1.15 per day (4.8%). On average, the intervention increased daily revenue by \$1.25 over the 60 days following the intervention—equivalent to a 5.2% uplift relative to control.

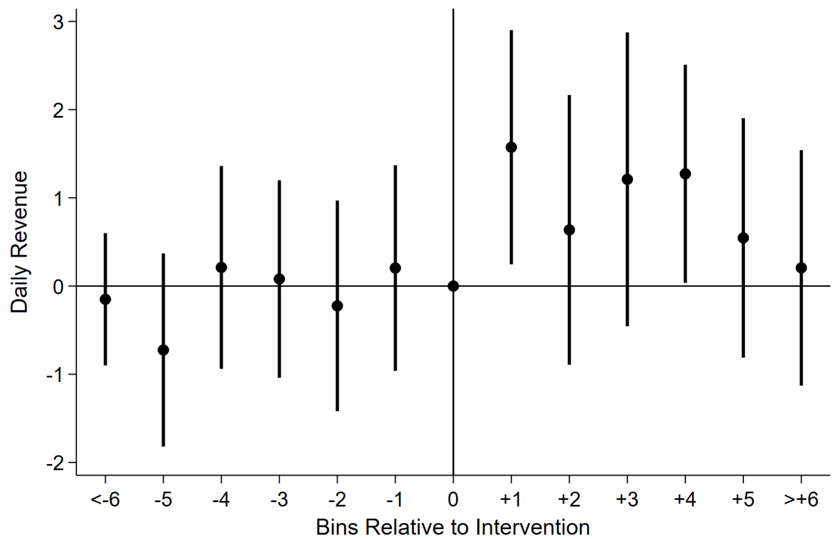
Table 1: Nudge Effects on Daily Revenue

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	1.11	2.27***	-0.05	1.15*	1.25**
	(0.68)	(0.71)	(1.58)	(0.60)	(0.57)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.093	0.001	0.972	0.047	0.023
Control mean	23.54	22.95	42.35	23.86	24.03
Obs.	9663	9663	9663	9663	9663

Note: Each column presents estimates based on Equation 1, regressing mean daily revenue in US dollars during the period indicated in the column title on an indicator for being assigned to the nudge group. Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the nudge and control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To grasp the full dynamics of the effect, Figure 3 plots the event-study coefficients obtained from Equation 2. Each coefficient corresponds to 14-day bins, with the 14 days before

Figure 3: Event-Study of Nudge Effects on Daily Revenue



Note: The plot presents event-study coefficients based on Equation 2, where the outcome variable is daily revenue in US dollars and the treatment variable is an indicator for being assigned to the nudge group. Time period bins correspond to 14 days. Period 0 corresponds to the 14 days before the start of the intervention. Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the nudge and control groups. 95% confidence intervals. Standard errors clustered at the firm level.

the onset of the intervention normalized to zero. Besides the impacts already discussed in Table 1, the plot allows to draw the following conclusions: First, there are no significant trends before the first round of messages, which further reinforces the evidence supporting that our estimates are unbiased. Second, we observe that effects fade away and fully disappear after roughly 60 days post intervention (from bin 5 onward), implying that the nudge had no meaningful effects in the longer run. This suggests that the experiment did not trigger lasting improvements in business practices nor it affected firm survival. This contrasts with traditional business training programs, which can often improve practices and performance for over one or two years, although at a high cost and with limited scalability (McKenzie, 2021).

Is the increase in revenue mostly explained by changes in prices or in quantities sold? Table A3 in the Appendix reports the effect of the nudge on daily units sold. The evidence indicates that most of the revenue gains originate from quantity rather than price: In the first week after the intervention, treated firms sold about 5.5% more units than control firms, although this difference is marginally insignificant. During the second week the gap widens to 9.1%, a highly significant increase. Like with revenue, the treatment effect turns indistinguishable from zero on the day of Black Friday, but it re-emerges in the subsequent period at an average of 4.3%. Cumulatively, over the entire 60-day window, treated firms sold 5.6% more units than their peers in the control group. Conversely, as will be discussed in Section 4.2.2, there is no evidence that the nudge affected prices.

An additional question is whether the nudge operates differently for firms with brick-and-mortar stores. This distinction matters both in its own right and because one might worry that our baseline estimates simply reflect a shift in sales from offline to online channels for firms with physical stores. Table A4 in the Appendix shows that, when the sample is limited to fully online firms, the results remain largely unchanged. In the first week after the intervention, the treatment effect is negligible; in the second week, treated firms' revenue rises by 10.9%. On Black Friday itself and in the period that follows, the estimates are imprecise but point to increases of 4.4% and 6.0%, respectively (the subsample is less than half the size of the baseline). Over the 60-day window, the average effect is 6.1%—roughly one percentage point larger than under the full sample.

Finally, to provide reassuring evidence that the poorly executed distribution of second-round messages in the Argentine subsample (discussed in Section 3.2) does not meaningfully influence the findings, Table A5 replicates the analysis using only Brazilian firms. The substantial reduction in sample size inevitably lowers statistical power; nevertheless, the qualitative conclusions remain unchanged. Revenue among treated firms rises by 9.6% in Week 2 and averages a 4.6% increase over the full 60-day period.

4.2 Mechanisms

This section taps on the richness of the data to uncover what changes in managerial planning were induced by the nudge that could explain the boost in sales. It shows evidence that advertising and inventory management played key roles in mediating the increase in revenue, while the pricing strategy remained unaffected by the treatment.

4.2.1 Advertising

The experiment sought to prompt managers to plan for Black Friday in advance, specifically mentioning advertising. Leveraging novel large-scale data on firms' Instagram activity, I examine whether the intervention changed advertising behavior. The results indicate that the nudge increased the likelihood that managers advertised discounts during the week preceding Black Friday—evidence consistent with more proactive planning.

Advertising is core to firms' operations. Most business training programs, such as the International Labour Organization's Start-and-Improve Your Business program (De Mel, McKenzie and Woodruff, 2014), devote an entire module to it, and recent interventions by Anderson and McKenzie (2022) and Jin and Sun (2024) do the same.Yet small firms in low- and middle-income countries often struggle: only 17% of the businesses studied by McKenzie and Woodruff (2017) engaged in any advertising, even though marketing practices were among the strongest predictors of performance, alongside record-keeping.

Advertising is especially critical for the online firms in this study. Because they sell through their own websites rather than on centralized marketplaces, they cannot rely on a platform to supply customers. Instead, they mainly use social media—particularly Instagram, which allows for free advertising in the form of posts. Ninety-five percent of sample firms maintain an Instagram account. While paid ads on social media or search engines are possible, they remain uncommon among businesses of this size.

Despite its importance, advance advertising for Black Friday is surprisingly rare. Although 75% of control-group firms offer discounts on the day itself, only 19% mention those discounts on Instagram at least once during the preceding week, and just 8% do so more than once. The daily probability of advertising a discount in that week is 4.8%. This low prevalence is not driven by a general aversion to posting: 64% of firms upload at least one post during the week leading up to Black Friday.

Leveraging data on Instagram activity, I explore whether the nudge affected advertising behavior. I first test whether the treatment altered posting frequency. Table A6 in the Appendix shows no economically or statistically significant effects, suggesting that firms were already posting at roughly their preferred rate and that the behavioral constraints addressed by the nudge are not binding.

Next, Table 2 analyzes post content by flagging captions that include discount-related terms.[4] I find that treated managers tend to substitute generic posts with discount-oriented posts during the week before Black Friday: The likelihood of advertising a discount rose by 15%, with no discernible differences before or after that period.

This shift is consistent with managers planning their advertising in advance—designing promotional materials several days early and thereby gaining an edge in customer acquisition. The timing of the uptick in strategic advertising aligns with the main revenue effects, suggesting that the advertising channel may have played a key role behind the observed sales gains.

[4]The list of terms includes: *black friday, fraidei, friday, viernes, ' cupon', ' cupom', ' desconto', ' promoção', ' promoções', ' descuento', ' promocion'.*

Table 2: Daily Likelihood of Advertising Discounts

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	0.001	0.007***	-0.001	0.001	0.002*
	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.625	0.003	0.905	0.238	0.082
Control mean	0.034	0.048	0.123	0.023	0.029
Obs.	9196	9196	9196	9196	9196

Note: Each column presents estimates based on Equation 1, regressing the mean of a daily indicator for mentioning discount-related terms in social media posts during the period indicated in the column title, on an indicator for being assigned to the nudge group. The sample includes firms assigned to the nudge and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Additionally, Figure A2 in the Appendix presents treatment effects in an event-study specification using 3-day bins, thereby allowing for some pre-treatment estimates. Reassuringly, none of the pre-event coefficients differs significantly between treatment and control. We also observe that the pattern remains flat in the longer run: the terminal coefficient—which pools all observations 30 to 120 days after the intervention—is virtually equal to zero. In line with the analogous event-study for revenue, the nudge therefore shows no discernible long-run impact on advertising.

4.2.2 Pricing

Besides advertising, the nudge aimed at promoting planning in terms of pricing, possibly the most fundamental strategy when it comes to a big sale event such as Black Friday. This section explores the impact of the nudge on prices from multiple perspectives, finding no evidence of an effect.

Table A7 in the Appendix uses the full product listings observed on Black Friday to estimate Equation 3. It tests three outcomes: (i) an indicator for whether the firm discounted any product, (ii) the log of the mean listed price, and (iii) the log of the standard deviation of listed prices (a proxy for price dispersion). I repeat the analysis for the full product range and for the top five products by quantities sold in the 90 days before the intervention.

Across all specifications, the estimated effects are small and statistically insignificant. Thus the nudge neither increased the share of firms offering discounts—already 75%—nor altered average prices and their dispersion. The finding reassures that the message did not supply novel information to managers, as there is no evidence that receiving the nudge increased participation in the event..

I complement the previous analysis by also looking at transacted prices and non-price promotions (*e.g.*, quantity- or threshold-based discounts). Figure A3 in the Appendix shows the evolution of prices at the product variant level, controlling for variant fixed effects and time period fixed effects (Equation 2). Coefficients remain near zero and never attain statistical significance, reinforcing the conclusion that the nudge did not impact on the pricing strategy of treated firms. Figure A4 performs the same exercise for non-price promotions and yields similarly negligible effects.

Taken together, these null results imply that managers are aware that Black Friday is approaching and plan their discounts in advance; otherwise, the reminder and call to action would have induced at least some firms at the margin to adjust prices. Importantly, the evidence speaks only to whether prices changed, not to how well they were set: even with full attention, managers could misprice because of other behavioral or informational frictions untouched by the nudge.

4.2.3 Inventory Management

Do managers respond only to the specific instructions contained in the nudge, or can the prompt generate broader, unanticipated changes in behavior? Evidence shows that, beyond the intended focus, managers also improve their inventory management ahead of the event—an essential business practice the intervention did not explicitly target. Inventory control is central to firm operations (Cachon, Gallino and Olivares, 2019), and several studies document its importance for small firms in less-developed settings (Kremer et al., 2013; Bloom et al., 2013; McKenzie and Woodruff, 2017). In the context of a major sales event such as Black Friday, inadequate stock can severely limit performance if firms run out of inventory. Despite this, 23% of control-group firms still stock out on at least one product on Black Friday, pointing to suboptimal planning.

Using the full product listings recorded on the day before Black Friday, Table 3 applies Equation 3 to estimate the nudge's effect on inventories. Because a stock-out automatically blocks sales on the platform, managers have strong incentives to keep quantities updated. Panel A analyzes product variants, and Panel B considers product categories (see Section 3.1

for details). Treated firms list 7% more variants and 6% more with positive stock than their peers in the control group. By contrast, the nudge leaves the stock position of top-selling variants unchanged, suggesting that managers were already planning adequately for their most popular products. Nor does it expand the number of product categories, implying that the message did not spark a deeper, more sophisticated process of expanding the types of products offered by the firm. In sum, the planning prompt led managers to bolster inventories for less salient variants, thus marginally reducing the risk of stock-outs.

Table 3: Log-Number of Product Variants and Categories

	Any Stock	Stock>0	
	(1)	(2)	(3)
	All	All	Top 5
Panel A: Product Variants			
Nudge	0.07**	0.06**	0.01
	(0.03)	(0.03)	(0.01)
Strata FE	Yes	Yes	Yes
RI p-value	0.014	0.035	0.489
Control mean	5.585	5.259	1.119
Obs.	9660	9633	8537
Panel B: Product Categories			
Nudge	0.04	0.00	0.01
	(0.03)	(0.03)	(0.01)
Strata FE	Yes	Yes	Yes
RI p-value	0.105	0.920	0.520
Control mean	4.766	4.216	1.216
Obs.	9664	9287	8397

Note: Each column presents estimates based on Equation 3. Column 1 regresses the log-number of products listed as of the day before Black Friday (BF) on an indicator for being assigned to the nudge group. Columns 2 and 3 regress the analogous considering only products with positive stock and products with positive stock that were among the top-5 most sold in the 90 days before the intervention, respectively. The sample includes firms assigned to the nudge and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A potential concern around the increase in inventories is that firms may have over-accumulated units, leading to inefficiencies and increased storage costs, ultimately squeezing profit margins. I falsify this possibility using the Instagram posts data: If treated firms had overstocked, they should be more likely to advertise stock clearance campaigns, especially in the aftermath of the event. However, Table A8 shows no such pattern; at every point in the observation window, treated and control firms advertise clearance sales at similar rates.

Taken together, these results are consistent with enhanced planning also around inventories: Managers who receive the nudge are more likely to expand inventories and update their product listings in time for the event, possibly preventing missed transactions as a consequence of running out of stocks. This unexpected finding—inventory management was not an explicit target—suggests a holistic managerial response and echoes recent laboratory findings that nudges can boost complementary, non-targeted behaviors (Altmann, Grunewald and Radbruch, 2024).

4.3 Treatment Effect Heterogeneity

This section uncovers heterogeneities in the effect of the nudge across different types of firms, introducing important nuances on the effectiveness of nudges to improve the performance of small firms. I proceed in two steps: First, I pin down the relevant moderators leveraging a machine learning procedure explained below. This process reveals that firm size is a crucial factor driving the effectiveness of the nudge, among other covariates. Thus, in the second step I combine the relevant firm size moderators into a Firm Size Index (FSI) to quantify its moderating power—that is, by how much the effect of the nudge changes with the FSI.

To identify what covariates affect the effectiveness of the nudge I follow Athey, Tibshirani and Wager (2019) and estimate a generalized random forest, which provides conditional average treatment effects (CATE) for each firm using all available covariates. I focus on predicting the 60-day effect. As opposed to standard heterogeneous effects explorations, a key advantage of this approach is that it agnostically incorporates all available information, saving the researcher from making the discretionary choice of what covariates to focus on. In the second step, I combine the relevant covariates to build an index and quantify how m

In the Appendix, Table A9 presents the results. I examine whether firm characteristics are different across the below median CATE and the above median CATE groups (Columns 1 and 2, respectively). Column 3 shows the differences in means and Column 4 provides the corresponding p-value adjusting for multiple hypothesis testing based on List, Shaikh and Xu (2019).

We observe a robust pattern: The nudge had a stronger effect on relatively larger firms, including those with higher pre-treatment revenue, which are older, with more employees, and with brick-and-mortar stores (or at least a showroom to display the products). Interestingly, more sophisticated firms benefit more from a simple behavioral intervention such as the messages. Moreover, results also indicate that the effect was stronger among firms with a stronger presence on social media (more likely to have Instagram and Facebook accounts, and a higher number of followers and posts before the intervention), suggesting that the advertising channel may have been especially important.

Another interesting pattern that involves sector, brick-and-mortar stores, and number of employees—all of which are self-reported variables—is that in all cases the share of non-respondents is significantly lower in the high CATE group. In the sector variable, the share of non-respondents falls from 30.3% in the low CATE group to 23.5% in the high CATE group; in physical stores, from 37.8% to 33.2%; and, in number of employees, from 46.5% to 40.8%. Conversely, there are significant increases in the share of firms that sell clothing or home & garden products, who have at least a showroom, and who have between 2 and 25 employees. The last two in particular indicate that the nudge was more effective among larger firms who also engage more with the Platform, which could reflect a higher likelihood of paying attention to its communications.

Finally, Argentine firms are significantly more likely than Brazilian firms to be in the upper half of the CATE distribution. Although there are multiple differences between the two countries, a major one in this context is how salient Black Friday is, as discussed in Section 2.2. In particular, BF is the single most important sales event in Brazil, while it is much smaller in Argentina (where Cyber Monday and the "Hot Sale" are the main ones). This suggests that Argentine managers are likely to be less attentive to BF than Brazilian ones, furthering the interpretation that the nudge operates by addressing limited memory and inattention.

Table 4: Heterogeneous Effects on Revenue by Firm Size Index

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	1.07	2.23***	-0.11	1.12*	1.22**
	(0.68)	(0.71)	(1.58)	(0.60)	(0.57)
Nudge x FSI	0.66	1.22*	0.33	1.43**	1.30**
	(0.68)	(0.72)	(1.59)	(0.60)	(0.57)
FSI	1.59***	2.23***	3.43***	1.10**	1.33***
	(0.55)	(0.58)	(1.29)	(0.48)	(0.46)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
Control mean	23.54	22.95	42.35	23.86	24.03
Obs.	9663	9663	9663	9663	9663

Note: Each column presents estimates based on Equation 1, regressing mean daily revenue in US dollars during the period indicated in the column title on an indicator for being assigned to the nudge group, the Firm Size Index (FSI), and an interaction between the two. The FSI is a standardized mean of pre-intervention revenue winsorized at the 99th percentile, firm age, an indicator for having 2 employees or more, an indicator for having at least a showroom, indicators for having Instagram and Facebook accounts, and number of Instagram followers and pre-intervention posts winsorized at the 99th percentile (Anderson, 2008). Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the nudge and control groups. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To quantify by how much the impact on revenue varies with firm size, I build a Firm Size Index (FSI) that combines all relevant covariates identified in the analysis above.[5] As expected, Table 4 reveals an economically and statistically meaningful interaction between the nudge and the FSI. Column 5 shows that firms that are one standard deviation above the mean in terms of the FSI enjoy an increase in revenue that is more than twice as large than the average effect. Because firms with higher FSI also sell more in general, this translates into a 9.9% increase in revenue with respect to the control group, compared to the average 5.2% identified in Table 1. In other words, the treatment effect of the nudge on firms that are one standard deviation above the mean in terms of the FSI was 9.9% on average throughout the

[5]The index is a standardized average of the following variables: pre-intervention revenue winsorized at the 99th percentile, firm age, an indicator for having 2 employees or more, an indicator for having at least a showroom, indicators for having Instagram and Facebook accounts, and number of Instagram followers and pre-intervention posts winsorized at the 99th percentile. The index is constructed following Anderson (2008).

60-day post-intervention period. We also observe, in Columns 2 and 4, that this advantage for larger firms is present in both periods were the nudge was effective—Week 2 and the post-Black Friday interval.

Finally, are the effects stronger because of a stronger first stage? That is, did larger firms react by advertising discounts and increasing inventories relatively more than smaller businesses? Tables A10, A11, and A12 show that this is not the case: Firms with a higher FSI did not behave significantly different in any of the mediator variables, including advertising discounts, inventories, and also pricing.

Taken together, the evidence suggests a strategic complementarity between light-touch interventions and firm size—very small firms often lack the complementary skills, know-how, customer base, and scale economies needed to benefit from such interventions. This is in line with recent work on small firms. For example, Otis et al. (2024) find that giving Kenyan micro-enterprises access to generative-AI tools helps only the larger firms at baseline, while Dai, Kim and Luca (2023) report that increased online advertising has stronger effects on restaurants that already have more clients and better reputations. These insights have important implications for policies aimed at supporting very small enterprises and may help explain why some past programs failed to produce sizable results (Cole, Joshi and Schoar, 2024; Tarozzi, Desai and Johnson, 2015; Karlan and Valdivia, 2011).

4.4 Additional Results

This section presents the results from the alternative messages, which involved an extension of the nudge to also include an explanation of the loss leader pricing strategy, in an attempt to explore the potential of combining a behavioral and an informational intervention. First, it shows that this treatment arm had a null impact on revenue. Second, it discusses possible mechanisms, providing suggestive evidence that managers who received these messages were less likely to pay attention and engage with it.

In Table A13 in the Appendix, we observe the effect of the longer messages on revenue. Coefficients tend to be very small—both in levels and in relative terms with respect to the control group—and statistically non-significant. In particular, throughout the 60-day post-intervention period, there is an average insignificant effect of $ -0.30 in daily revenue. Tables A14 and A16 present the corresponding analyses on advertising and inventory management, with little differences with respect to the nudge overall. Importantly, we also observe little effects on pricing (Table A15), especially in terms of price dispersion (columns 3 and 6), where we would expect an increase if managers had adopted the loss-leader strategy.

Why didn't the alternative message affect revenue? One key difference between the two messages lies in managers' participation in the raffle. As detailed in Section 3.2, each manager could submit the image or flyer they planned to use for their main Black Friday discount and thereby enter a drawing for one of three tablets. Importantly, the raffle invitation appeared only at the end of each message. Participation rates diverged: 2.03% of managers in the nudge group submitted a flyer, compared with 1.45% in the alternative message group—a 29% drop (p-value=0.030). This pattern suggests that the alternative message's additional explanation of the loss-leader strategy—making the communication longer and arguably more cognitively demanding—reduced manager engagement. Indeed, recent evidence supports the idea that shorter, simpler messages outperform longer, more complex ones (Shulman, Markowitz and Rogers, 2024; Cortes et al., 2021). The ineffectiveness of this treatment arm further adds evidence on the influence that behavioral frictions can exert on managerial decision-making in small firms.

5 Conclusion

Business practices are a crucial input of the firm's production function. A growing literature has found mixed evidence on whether different types of interventions promoting good practices—mainly in the form of training programs—can be beneficial for firms in developing countries. However, there is little evidence on whether simple, behavioral treatments can improve practices and firm performance.

This paper underscores the importance of behavioral frictions as a meaningful constraint on operational planning and firm performance among small businesses. It presents the results of an experiment with a large sample of Argentine and Brazilian firms, testing whether a messaging intervention directed to managers of small e-commerce businesses can improve firm performance around Black Friday, a major business opportunity. The main result shows that nudging managers to plan their operations for the event resulted in 5.2% higher revenue over a period of 60 days, mainly driven by a 9.9% increase during the week before BF. Evidence on mechanisms is consistent with enhanced planning: Treated managers implemented more effective social media advertising and inventory strategies. Importantly, larger firms with stronger social media presence benefited the most from the intervention, suggesting that firm size is a strategic complement to light-touch interventions.

E-commerce platforms and policymakers aiming to support small firms may consider helping managers and entrepreneurs to reduce the impact of attention and memory constraints.

This adds to well-established evidence that nudges are a cost-effective way of improving outcomes among households (Benartzi et al., 2017). Simple, cost-effective prompts can offer a way to temporarily enhance business practices and firm performance, opening windows of opportunity when properly timed around important events. Nevertheless, the effectiveness of such interventions can be contingent on the characteristics of firms, mainly in terms of firm size, with relatively larger firms being more capable of unlocking the benefits. This implies that alleviating constraints among entrepreneurs who are most in need of help may require more involved and tailored solutions. Ultimately, the insights from this paper contribute to our understanding of the nuanced conditions under which behavioral interventions enhance firm performance, guiding future policy and practice aimed at supporting small enterprises.

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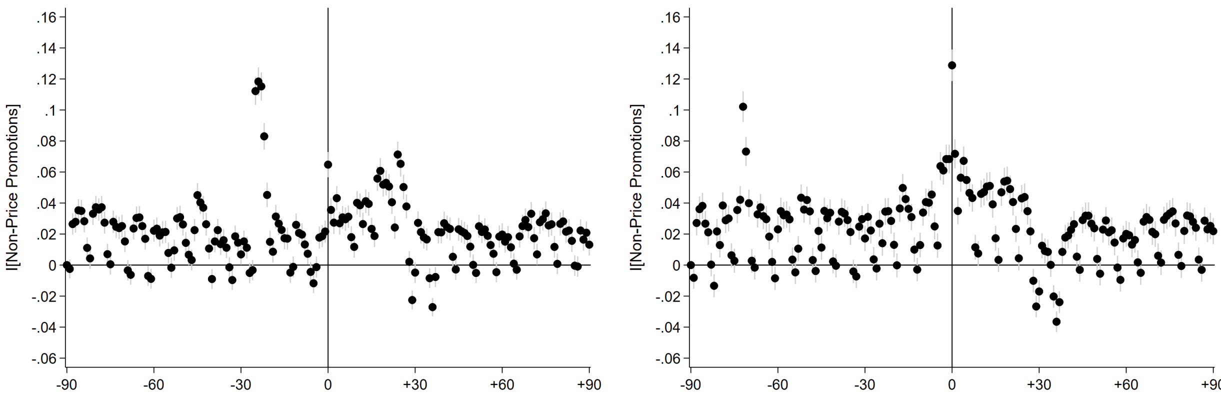
A Appendix

A.1 Context

Figure A1: Daily Evolution of Non-Price Promotions Around Black Friday



(a) Argentina **(b)** Brazil

Note: Each plot presents event-study coefficients where the outcome variable is an indicator for having transactions with non-price promotions (quantity- or threshold-based discounts). Each coefficient corresponds to a day before/after Black Friday (period 0). The coefficient for period -90 is normalized to zero.

A.2 Methods

Table A1: Sample characteristics

	N	mean	sd	median	min	max
Sales Aug-Oct '21	14494	1633.95	4106.39	728	0	319904
Months since entry	14494	22.96	19.79	16	1	122
Microfirm	8168	0.91	0.29	1	0	1
Online only	9372	0.65	0.48	1	0	1
Clothing	10601	0.51	0.50	1	0	1
Home & Garden	10601	0.07	0.25	0	0	1
Health & Beauty	10601	0.07	0.25	0	0	1
Food & Drinks	10601	0.04	0.21	0	0	1
Art & Antiques	10601	0.04	0.20	0	0	1
Other	10601	0.27	0.44	0	0	1
Instagram	14494	0.95	0.21	1	0	1
Facebook	14494	0.72	0.45	1	0	1
Google Analytics	14494	0.40	0.49	0	0	1
Integrated apps	14494	4.43	2.79	4	1	41
Country=AR	14494	0.53	0.50	1	0	1
Country=BR	14494	0.47	0.50	0	0	1

This table presents summary statistics for the main covariates observed in the data. *Sales Aug-Oct '21* include total revenue in US dollars in that period. *Months since entry* are counted since opening the website on the platform. *Microfirm* is an indicator for reporting to have at most 5 full time employees. *Online only* is an indicator for reporting no brick-and-mortar stores. Sector indicators include *Clothing, Home & Garden, Health & Beauty, Food & Drinks, Art & Antiques* and *Other*. *Instagram* and *Facebook* are indicators for having Instagram or Facebook accounts linked to the store. *Google Analytics* is an indicator for having integrated such tool to the store. *Integrated apps* is the total number of third-party apps integrated to the store, besides Google Analytics.

Table A2: Balance table

	Treatment 1			Treatment 2		
	(1)	(2)	(3)	(4)	(5)	(6)
Sales Aug-Oct '21	0.000	0.000	0.000	0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Months since entry	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
0-1 employees		-0.005	-0.005		-0.006	-0.007
		(0.013)	(0.013)		(0.013)	(0.013)
2-5 employees		-0.003	-0.004		-0.008	-0.010
		(0.014)	(0.014)		(0.014)	(0.014)
6-25 employees		-0.021	-0.021		0.053**	0.052**
		(0.023)	(0.023)		(0.023)	(0.023)
25+ employees		0.011	0.011		0.036	0.035
		(0.042)	(0.043)		(0.042)	(0.043)
0 B&M		-0.007	-0.008		0.007	0.008
		(0.015)	(0.015)		(0.015)	(0.015)
Showroom only		-0.018	-0.018		0.010	0.011
		(0.018)	(0.018)		(0.018)	(0.018)
1 B&M		-0.001	-0.001		0.020	0.021
		(0.016)	(0.016)		(0.016)	(0.016)
2-5 B&M		0.009	0.008		-0.024	-0.023
		(0.026)	(0.026)		(0.026)	(0.026)
5+ B&M		-0.005	-0.006		-0.012	-0.010
		(0.066)	(0.066)		(0.066)	(0.066)
Clothing		0.006	0.006		-0.005	-0.005
		(0.015)	(0.015)		(0.015)	(0.015)
Home & Garden		0.006	0.007		-0.003	-0.002
		(0.022)	(0.022)		(0.022)	(0.022)
Health & Beauty		0.006	0.007		-0.007	-0.007
		(0.023)	(0.023)		(0.023)	(0.023)
Food & Drinks		0.007	0.008		-0.011	-0.010
		(0.026)	(0.026)		(0.026)	(0.026)
Art & Antiques		0.012	0.012		-0.032	-0.032
		(0.027)	(0.027)		(0.027)	(0.027)
Other		0.005	0.005		-0.006	-0.006
		(0.017)	(0.017)		(0.017)	(0.017)
Instagram			0.011			-0.024
			(0.019)			(0.019)
Facebook			-0.005			-0.000
			(0.010)			(0.010)
Google Analytics			-0.001			-0.004
			(0.009)			(0.009)
Integrated apps			0.001			0.002
			(0.002)			(0.002)
Country=AR			0.001			0.002
			(0.009)			(0.009)
Control mean	0.33	0.33	0.33	0.33	0.33	0.33
F-test p-value	0.73	1.00	1.00	0.92	0.65	0.77
Obs.	14494	14494	14494	14494	14494	14494

A.2.1 The Second Message (T2)

Below is the text from the message assigned to the second treatment arm:

Black Friday is just around the corner! Take advantage of this event to increase your sales and participate in a raffle to win one of three iPads. If you want to participate, read the following message carefully.

Black Friday (Nov-26) is a great opportunity to increase sales by offering discounts and promotions for a short period of time. Have you already planned yours? We know it is a difficult decision, so we bring you this advice that may be useful.

Depending on the characteristics of your business, it may be a mistake to discount a large number of your products. Sometimes it is better to choose just one of them and give it an irresistible discount, between 60-80%. The goal of this strategy is to draw attention, attract customers to your store, and get them to buy other products at full price. This strategy also serves to increase your customer base in the long run, as many more people will become familiar with your brand.

Keep in mind that this strategy is not best for everyone. It tends to work best for stores that are looking to build customer loyalty, and when the discounted product is usually purchased in conjunction with others in the store.

At the same time, don't forget to communicate your discounts and promotions on social media. You can offer great things, but if your audience doesn't know about them, they won't have any impact, so don't miss the opportunity!

To participate in the raffle for one of three iPads, just send the flyer you will use to promote your main Black Friday discount. You have time until Nov-25!

A.3 Revenue

Table A3: Daily Quantities Sold

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	0.07	0.12***	0.02	0.06*	0.07**
	(0.04)	(0.04)	(0.10)	(0.03)	(0.03)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.096	0.005	0.871	0.081	0.041
Control mean	1.27	1.32	2.48	1.23	1.26
Obs.	9660	9660	9660	9660	9660

Note: Each column presents estimates based on Equation 1, regressing mean daily units sold during the period indicated in the column title on an indicator for being assigned to the nudge group. Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the nudge and control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Nudge Effects on Daily Revenue, Online Firms Only

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	0.52	2.38**	1.79	1.34	1.38
	(1.01)	(1.06)	(2.40)	(0.89)	(0.85)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.600	0.024	0.452	0.132	0.105
Control mean	22.23	21.93	41.11	22.36	22.61
Obs.	4063	4063	4063	4063	4063

Note: Each column presents estimates based on Equation 1, regressing daily revenue in US dollars during the period indicated in the column title on an indicator for being assigned to the nudge group. Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the nudge and control groups with no brick-and-mortar stores. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A5: Nudge Effects on Daily Revenue, Brazilian Firms Only

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	0.32	2.29**	0.34	0.73	0.86
	(0.93)	(1.07)	(2.33)	(0.78)	(0.77)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.720	0.030	0.910	0.360	0.250
Control mean	20.60	23.95	43.30	18.76	19.99
Obs.	4546	4546	4546	4546	4546

Note: Each column presents estimates based on Equation 1, regressing daily revenue in US dollars during the period indicated in the column title on an indicator for being assigned to the nudge group. Revenue is winsorized at the 99th percentile. The sample includes Brazilian firms assigned to the nudge and control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

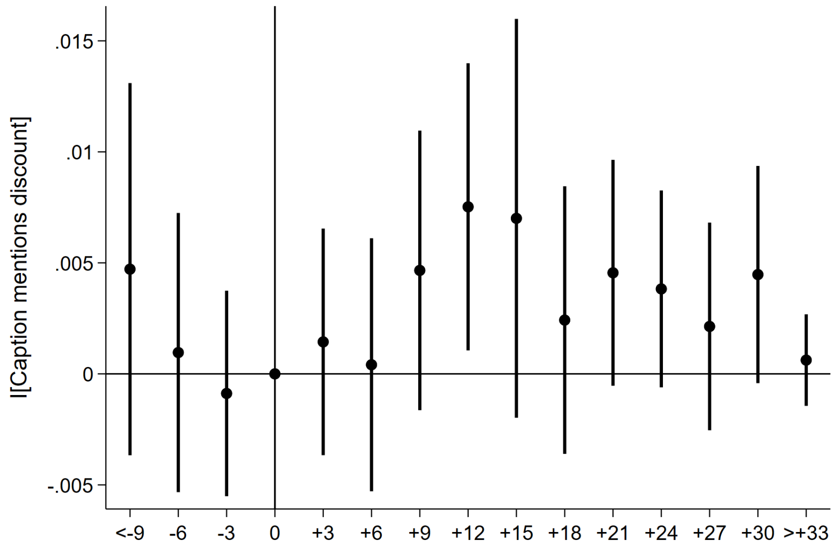
A.4 Advertising

Table A6: Daily Likelihood of Posting

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	-0.003	0.002	-0.001	0.002	0.001
	(0.004)	(0.004)	(0.008)	(0.003)	(0.003)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.332	0.583	0.901	0.567	0.684
Control mean	0.267	0.269	0.313	0.240	0.247
Obs.	9196	9196	9196	9196	9196

Note: Each column presents estimates based on Equation 1, regressing the mean of a daily indicator for posting in social media during the period indicated in the column title, on an indicator for being assigned to the nudge group. The sample includes firms assigned to the nudge and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A2: Advertising Discounts



Note: The plot presents event-study coefficients based on Equation 2, where the outcome variable is a daily indicator for mentioning discount-related terms in social media posts and the treatment variable is an indicator for being assigned to the nudge group. Time period bins correspond to 3 days. Period 0 corresponds to the 3 days before the start of the intervention. The sample includes firms assigned to the nudge and control groups. 95% confidence intervals. Standard errors clustered at the firm level.

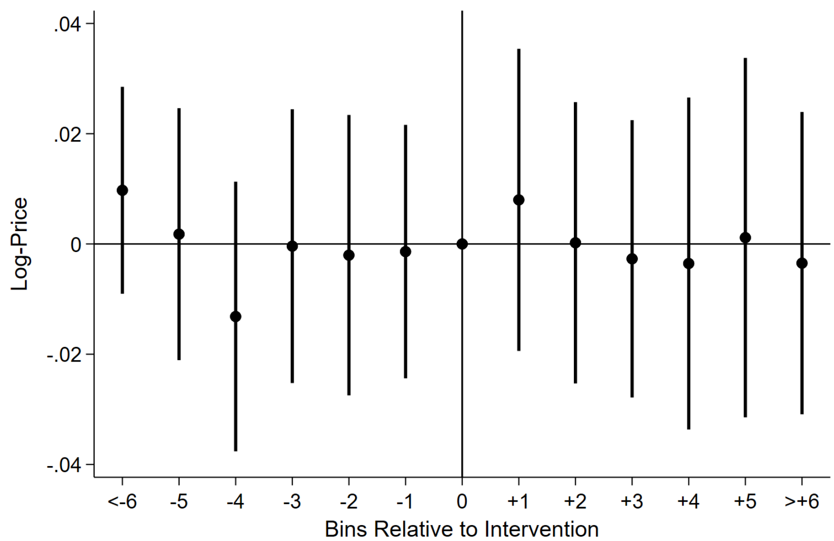
A.5 Pricing

Table A7: Pricing, Black Friday Listings

	Full Listing			Top 5 Variants		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any disc.	Log(Avg P)	Log(σ)	Any disc.	Log(Avg P)	Log(σ)
Nudge	0.010	-0.006	-0.023	0.015	-0.019	-0.039
	(0.009)	(0.020)	(0.024)	(0.010)	(0.022)	(0.030)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
RI p-value	0.266	0.761	0.356	0.137	0.392	0.188
Control mean	0.748	6.284	5.769	0.392	6.034	5.033
Obs.	9664	9659	9594	9664	9414	8565

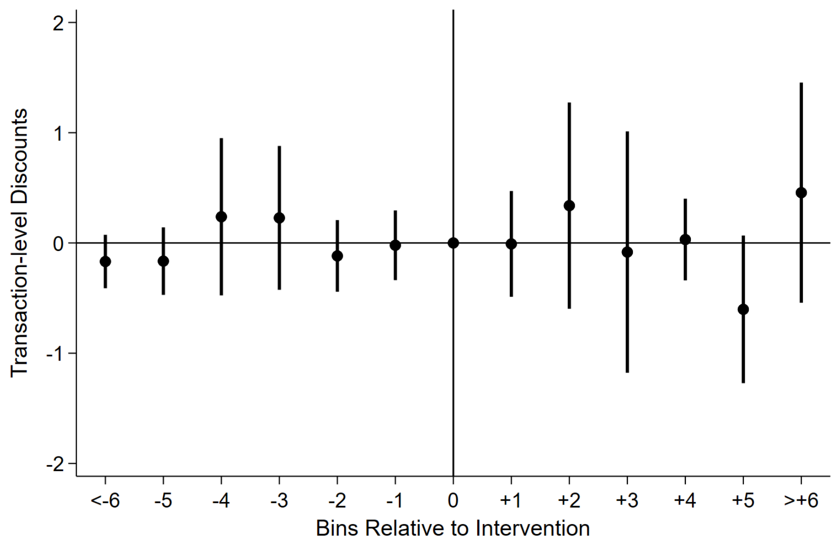
Note: Each column presents estimates based on Equation 3. Columns 1–3 consider all product variants and columns 4–6 consider the five most sold product variants only, based on quantities sold during the 90 days before the intervention. All prices correspond to the day of Black Friday. The outcome in columns 1 and 4 is an indicator for having any product variant under discount. The outcome in columns 2 and 5 is the log of the average price. The outcome in columns 3 and 6 is the log of the standard deviation of prices. The regressor of interest is an indicator for being assigned to the nudge. The sample includes firms assigned to the nudge and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A3: Event-Study of Nudge Effects on Transacted Prices



Note: The plot presents event-study coefficients based on Equation 2, where the outcome variable is the daily log-price of transacted product variants and the treatment variable is an indicator for being assigned to the nudge group. Time period bins correspond to 14 days. Period 0 corresponds to the 14 days before the start of the intervention. Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the nudge and control groups. 95% confidence intervals. Standard errors clustered at the firm level.

Figure A4: Non-Price Promotions



Note: The plot presents event-study coefficients based on Equation 2, where the outcome variable is total daily discounts in US dollars, excluding price-related discounts, and the treatment variable is an indicator for being assigned to the nudge group. Time period bins correspond to 14 days. Period 0 corresponds to the 14 days before the start of the intervention. Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the nudge and control groups. 95% confidence intervals. Standard errors clustered at the firm level.

A.6 Inventory management

Table A8: Mentioning Stock Clearances in Instagram Posts

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	-0.001	-0.001	-0.003	-0.001	-0.001
	(0.001)	(0.001)	(0.004)	(0.001)	(0.001)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.213	0.696	0.434	0.398	0.290
Control mean	0.019	0.022	0.035	0.019	0.019
Obs.	9196	9196	9196	9196	9196

Note: Each column presents estimates based on Equation 1, regressing the mean of a daily indicator for mentioning clearance-related terms in social media posts during the period indicated in the column title, on an indicator for being assigned to the nudge group. The list of terms includes: *liquid, clearance, ultim, agot, stock, inventario, queim, esgot, estoque*. The sample includes firms assigned to the nudge and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.7 Heterogeneity

Table A9: Conditional Average Treatment Effects on Revenue

Variable	(1) Low Predicted TE	(2) High Predicted TE	(3) Diff.	(4) MHT p-value
Pre-int. Revenue	14.820	24.842	10.022***	0.000
Firm age (months)	18.555	27.282	8.727***	0.000
Employees: 0-1	0.315	0.309	-0.006	0.974
Employees: 2-5	0.181	0.226	0.045***	0.000
Employees: 6-25	0.030	0.046	0.016***	0.000
Employees: 25+	0.008	0.011	0.003	0.837
Employees: N/A	0.465	0.408	-0.057***	0.000
Brick & Mortars: 0	0.339	0.308	-0.031***	0.001
Brick & Mortars: showroom	0.085	0.109	0.024***	0.000
Brick & Mortars: 1	0.169	0.203	0.034***	0.000
Brick & Mortars: 2-5	0.026	0.044	0.018***	0.000
Brick & Mortars: 5+	0.004	0.005	0.001	0.987
Brick & Mortars: N/A	0.378	0.332	-0.046***	0.000
Ind: Clothing	0.303	0.391	0.088***	0.000
Ind: Home & Garden	0.043	0.058	0.015**	0.015
Ind: Health & Beauty	0.054	0.045	-0.009	0.369
Ind: Food & Drinks	0.038	0.026	-0.012***	0.000
Ind: Art & Antiques	0.031	0.033	0.002	0.915
Ind: Gifts	0.026	0.029	0.004	0.953
Ind: Jewelry	0.025	0.026	0.002	0.966
Ind: Books	0.022	0.016	-0.006	0.342
Ind: Toys	0.016	0.014	-0.002	0.979
Ind: Electronics	0.013	0.010	-0.002	0.962
Ind: Sports	0.012	0.012	-0.000	0.934
Ind: Other	0.115	0.105	-0.011	0.723
Ind: N/A	0.303	0.235	-0.068***	0.000
Apps integrated	2.423	2.465	0.043	0.982
Instagram account	0.938	0.970	0.032***	0.000
Instagram followers	6,757	19,282	12,525***	0.000
Pre-int. Posts	4.032	5.139	1.107***	0.000
Facebook account	0.694	0.756	0.063***	0.000
Google Analytics	0.401	0.406	0.005	0.825
Country: Argentina	0.491	0.568	0.078***	0.000
Observations	4,832	4,831	9,663	

Note: This table characterizes, in columns 1 and 2 respectively, the subsample below and above the median predicted conditional average treatment effect (CATE) of the nudge on revenue during the 60 days after the intervention. CATEs are obtained by estimating a generalized random forest, following Athey, Tibshirani and Wager (2019). Column 3 provides the difference in means and column 4 the corresponding p-values adjusting for multiple hypothesis testing, following List, Shaikh and Xu (2019). The sample includes firms assigned to the nudge and the control groups. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Heterogeneity in Advertising Discounts, by Firm Size Index

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Nudge	0.001	0.007***	-0.001	0.001	0.002
	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)
Nudge x FSI	-0.003	-0.003	-0.003	0.002	0.000
	(0.002)	(0.003)	(0.007)	(0.001)	(0.001)
FSI	0.003*	0.011***	0.034***	0.003***	0.004***
	(0.002)	(0.002)	(0.006)	(0.001)	(0.001)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
Control mean	0.034	0.048	0.123	0.023	0.029
Obs.	9195	9195	9195	9195	9195

Note: Each column presents estimates based on Equation 1, regressing the mean of a daily indicator for mentioning discount-related terms in social media posts during the period indicated in the column title, on an indicator for being assigned to the nudge group, the Firm Size Index (FSI), and an interaction between the two. The FSI is a standardized mean of pre-intervention revenue winsorized at the 99th percentile, firm age, an indicator for having 2 employees or more, an indicator for having at least a showroom, indicators for having Instagram and Facebook accounts, and number of Instagram followers and pre-intervention posts winsorized at the 99th percentile (Anderson, 2008). The sample includes firms assigned to the nudge and control groups. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Heterogeneity in Pricing, by Firm Size Index

	Full Listing			Top 5 Variants		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any disc.	Log(Avg P)	Log(σ)	Any disc.	Log(Avg P)	Log(σ)
Nudge	0.013	-0.006	-0.027	0.015*	-0.009	-0.042
	(0.009)	(0.019)	(0.024)	(0.009)	(0.025)	(0.036)
Nudge x FSI	-0.006	-0.018	0.004	-0.002	-0.013	0.004
	(0.009)	(0.020)	(0.024)	(0.009)	(0.025)	(0.036)
FSI	0.017**	0.136***	0.189***	-0.014**	0.088***	0.093***
	(0.007)	(0.015)	(0.018)	(0.007)	(0.019)	(0.028)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.725	6.264	5.733	0.312	5.995	4.948
Obs.	9662	9633	9552	9662	8514	6729

Note: Each column presents estimates based on Equation 3. Columns 1–3 consider all product variants and columns 4–6 consider the five most sold product variants only, based on quantities sold during the 90 days before the intervention. All prices correspond to the day of Black Friday. The outcome in columns 1 and 4 is an indicator for having any product variant under discount. The outcome in columns 2 and 5 is the log of the average price. The outcome in columns 3 and 6 is the log of the standard deviation of prices. The regressors of interest are an indicator for being assigned to the nudge, the Firm Size Index (FSI), and an interaction between the two. The FSI is a standardized mean of pre-intervention revenue winsorized at the 99th percentile, firm age, an indicator for having 2 employees or more, an indicator for having at least a showroom, indicators for having Instagram and Facebook accounts, and number of Instagram followers and pre-intervention posts winsorized at the 99th percentile (Anderson, 2008). The sample includes firms assigned to the nudge and control groups. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Heterogeneity in Log-Number of Product Variants and Categories, by Firm Size Index

	Any Stock	Stock>0	
	(1)	(2)	(3)
	All	All	Top 5
Nudge	0.06**	0.06*	0.01
	(0.03)	(0.03)	(0.01)
Nudge x FSI	-0.03	-0.05	0.01
	(0.03)	(0.03)	(0.01)
FSI	0.33***	0.32***	-0.03***
	(0.02)	(0.02)	(0.01)
Strata FE	Yes	Yes	Yes
Control mean	5.58	5.26	1.12
Obs.	9659	9632	8537

Note: Each column presents estimates based on Equation 3. Column 1 regresses the log-number of products listed as of the day before Black Friday (BF) on an indicator for being assigned to the nudge group, the Firm Size Index (FSI), and an interaction between the two. The FSI is a standardized mean of pre-intervention revenue winsorized at the 99th percentile, firm age, an indicator for having 2 employees or more, an indicator for having at least a showroom, indicators for having Instagram and Facebook accounts, and number of Instagram followers and pre-intervention posts winsorized at the 99th percentile (Anderson, 2008). Columns 2 and 3 regress the analogous considering only products with positive stock and products with positive stock that were among the top-5 most sold in the 90 days before the intervention, respectively. The sample includes firms assigned to the nudge and control groups. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A.8 Additional Results

Table A13: Alternative Message Effects on Daily Revenue

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Alt. Message	-0.79	-0.16	-2.06	-0.21	-0.30
	(0.63)	(0.65)	(1.54)	(0.57)	(0.53)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.240	0.750	0.180	0.640	0.530
Control mean	23.54	22.95	42.35	23.86	24.03
Obs.	9658	9658	9658	9658	9658

Note: Each column presents estimates based on Equation 1, regressing mean daily revenue in US dollars during the period indicated in the column title on an indicator for being assigned to the alternative message group. Revenue is winsorized at the 99th percentile. The sample includes firms assigned to the alternative message and control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Alternative Message Effects on Advertising

	(1) Week 1	(2) Week 2	(3) BF day	(4) Post-BF	(5) Total (60 days)
Alt. Message	0.002	0.006***	0.001	0.001	0.002
	(0.002)	(0.002)	(0.007)	(0.001)	(0.001)
Pre-Int. Outcome	Yes	Yes	Yes	Yes	Yes
Strata FE	Yes	Yes	Yes	Yes	Yes
RI p-value	0.250	0.010	0.900	0.280	0.110
Control mean	0.034	0.048	0.123	0.023	0.029
Obs.	9178	9178	9178	9178	9178

Note: Each column presents estimates based on Equation 1, regressing the mean of a daily indicator for mentioning discount-related terms in social media posts during the period indicated in the column title, on an indicator for being assigned to the alternative message group. The sample includes firms assigned to the alternative message and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A15: Alternative Message Effects on Pricing

	Full Listing			Top 5 Variants		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any disc.	Log(Avg P)	Log(σ)	Any disc.	Log(Avg P)	Log(σ)
Alt. Message	0.017**	0.007	0.030	-0.006	-0.025	-0.015
	(0.009)	(0.020)	(0.025)	(0.010)	(0.023)	(0.030)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.748	6.284	5.769	0.392	6.034	5.033
Obs.	9660	9656	9594	9660	9418	8566

Note: Each column presents estimates based on Equation 3. Columns 1–3 consider all product variants and columns 4–6 consider the five most sold product variants only, based on quantities sold during the 90 days before the intervention. All prices correspond to the day of Black Friday. The outcome in columns 1 and 4 is an indicator for having any product variant under discount. The outcome in columns 2 and 5 is the log of the average price. The outcome in columns 3 and 6 is the log of the standard deviation of prices. The regressor of interest is an indicator for being assigned to the alternative message. The sample includes firms assigned to the alternative message and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A16: Alternative Message Effects on Inventories

	Any Stock	Stock>0	
	(1)	(2)	(3)
	All	All	Top 5
Panel A: Product Variants			
Alt. Message	0.05*	0.04	-0.00
	(0.03)	(0.03)	(0.01)
Strata FE	Yes	Yes	Yes
Control mean	5.58	5.26	1.12
Obs.	9657	9636	8543
Panel B: Product Categories			
Alt. Message	0.04*	0.02	0.01
	(0.03)	(0.03)	(0.01)
Strata FE	Yes	Yes	Yes
Control mean	4.77	4.22	1.22
Obs.	9660	9317	8417

Note: Each column presents estimates based on Equation 3. Column 1 regresses the log-number of products listed as of the day before Black Friday (BF) on an indicator for being assigned to the alternative message group. Columns 2 and 3 regress the analogous considering only products with positive stock and products with positive stock that were among the top-5 most sold in the 90 days before the intervention, respectively. The sample includes firms assigned to the alternative message and the control groups. Randomization inference (RI) p-value is based on 10,000 permutations. Control mean corresponds to the average outcome for the control group. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.