Nudges, Managerial Planning, and Small Firm Performance: Evidence from Online Commerce*

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Abstract

This paper provides experimental evidence that nudging managers to plan in advance for a business opportunity can improve firm performance. I leverage an experiment involving 9,700 small e-commerce firms in Argentina and Brazil, which took place during the two weeks before Black Friday (BF), a major sales event. The intervention consisted of randomizing messages reminding managers that BF was approaching and encouraging them to plan their pricing and advertising strategies. Consistent with enhanced planning, treated firms shifted from generic to discount-related advertising and increased their inventories before the event. This led to a 4% increase in sales for 20 to 60 days post-intervention. A causal forest estimation shows that the effects were stronger among relatively larger firms that use search engine optimization (SEO) tools, suggesting that pre-established capabilities may be a complement to light touch interventions.

JEL Codes: D22, D91, O12

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1 Introduction

Managers play a crucial role within firms. They plan, organize, and allocate resources to achieve organizational objectives. Indeed, there is growing evidence that managerial and business practices significantly influence firm productivity (Bloom and Van Reenen, 2007, 2010; McKenzie and Woodruff, 2017). This is particularly important in developing countries, where a substantial share of income and employment is generated by small, less productive firms.[1] Although research has shown that informational barriers can prevent the adoption of better practices (McKenzie, 2021), there is little evidence on the prevalence of behavioral frictions in this process and how to mitigate them.[2]

This paper presents experimental evidence that managers respond to a nudge designed to promote planning in advance of a major business opportunity, leading to higher firm performance. Specifically, I leverage a randomized controlled trial (RCT) involving 9,664 small online retailers in Argentina and Brazil, two of the largest economies in Latin America. The intervention consisted of distributing messages to firm managers, encouraging them to plan their pricing and advertising strategies for Black Friday (BF) 2021. Each manager received the message twice in the two weeks leading up to the event. The communications included a reminder that BF was approaching, cues to plan their discounts and to advertise them on social media, and a small incentive to increase salience: Managers who submitted a flyer promoting their BF discounts by the evening before the event were entered into a raffle to win one of three tablets.

Using rich data on sales, product listings, social media advertising, and firm characteristics, I find that treated firms display approximately 4% higher revenue during the 20 to 60 days following the onset of the intervention, with the effects fading out thereafter. Decomposing the evolution of revenue into prices and quantities reveals that the increase is driven by the latter, while prices remained unaffected on average. This is corroborated with price data on all listed products the day of BF, also implying that the nudge did not affect participation in the event. Moreover, to the extent that treatmentdid not affect the cost structure of businesses, profits may have increased by a similar rate than revenue. All estimates correspond to intent-to-treat effects, where 72% of managers read the message at

[1] Around 80% of individuals in low and lower middle income countries are self employed or work in firms with less than 10 employees, compared to 35% in upper middle and high income countries (ILO, 2019).

[2] A standard argument against focusing on behavioral frictions is that behaviorally constrained firms would not survive in competitive markets. However, at least in emerging economies, there exist multiple forces that allow less productive firms to survive, including informality, credit constraints, and other entry barriers lowering competition (La Porta and Shleifer, 2014; Kremer, Rao and Schilbach, 2019).

least once, and are robust to alternative specifications, including the use of a log-transformed outcome and the presence of outliers (Chen and Roth, 2023).

Turning to mechanisms, results show that the nudge successfully encouraged planning, impacting both targeted and non-targeted behaviors—specifically, advertising and inventory management. In the week preceding BF, treated firms are more likely to advertise discounts on social media (16%), although not increasing the total number of posts. Additionally, these firms exhibited a 6–11% increase in the number of products listed as in stock.

I also employ machine learning methods to uncover heterogeneities in treatment effects across different types of firms. Using all available covariates, I predict firm-specific Conditional Average Treatment Effects (CATE) following Athey, Tibshirani and Wager (2019) causal forest approach. I find that the nudge had stronger effects on larger and more experienced firms, particularly those with higher pre-treatment sales, those more likely to have physical stores or a showroom, and those that are older. Additionally, firms using Google Analytics, a Search Engine Optimization (SEO) tool, also experienced more pronounced effects. These results suggest that pre-existing firm and managerial capabilities are crucial for reacting effectively to the nudge and reaping its benefits. This embeds important lessons on the power of nudges to affect very small and simple businesses.

Why did the nudge affect behavior? I argue that the evidence is broadly consistent with having helped managers overcome limited attention and memory constraints. Firstly, there is no evidence that the intervention affected pricing dynamics, suggesting that managers were already aware of Black Friday's existence. Therefore, the nudge does not seem to have alleviated informational frictions in this regard. As mentioned above, the nudge was also more effective among older firms, who are more likely to have experienced Black Friday before. Secondly, the raffle did not alter the incentive structure for managers, as the expected monetary value for participating was only \$0.12. Indeed, engagement with the raffle was minimal: less than 2% of managers submitted a flyer, despite 35% of them having advertised discounts on social media at least once between the intervention and the event. Lastly, the message featured a reminder that BF was approaching and language that made salient the importance of the event, which can help managers overcome attention or memory constraints.

This paper makes the following contributions. First, it contributes to the literature documenting the importance of business and managerial practices (McKenzie and Woodruff, 2017; Bloom and Van Reenen, 2007). This line of work has 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). This study contributes with the insight that a fully behavioral treatment can improve business planning and lead to better performance during a short, but valuable period. Moreover, this paper shows that messages are a cheap and scalable intervention that can be an effective tool for helping small firms adopt better practices (McKenzie, 2021), although with the important caveat that they were more useful for relatively larger and more experienced firms. In particular, nudges and pre-established capabilities operate as complements, which embeds important lessons for policymakers that hope to improve the livelihoods of micro-entrepreneurs running very small and simple businesses.

Second, the present work offers novel experimental evidence that behavioral frictions can prevent managers from planning in advance of a major business opportunity, negatively affecting firm performance. This finding adds to a large literature on behavioral corporate finance, which has mainly focused on overconfidence among CEOs of large firms (Malmendier and Tate, 2005; Gervais, Heaton and Odean, 2011; Hirshleifer, Low and Teoh, 2012), but also covers present bias (Grenadier and Wang, 2005; Graham, Harvey and Puri, 2013), the sunk cost fallacy (Guenzel, forthcoming), and failure to incorporating competitor's actions into the expectation formation process (Greenwood and Hanson, 2015). This result also adds to recent work studying "behavioral firms," which has focused on developing countries and shows that firms often fail to maximize profits (Kremer, Rao and Schilbach, 2019; Seither, 2021; Banerjee et al., 2023). In particular, this paper complements Gertler et al. (2023), who show that distrust and memory constraints can prevent small Mexican firms from accepting a service fee reduction without a cost. Here, I present evidence consistent with limited attention and memory constraints being important barriers for the adoption of profitable practices—specifically, planning—in advance of a major business opportunity. Alternatively, Karlan et al. (2016) provides experimental evidence on the power of reminders to address limited attention to exceptional expenses impact household behavior on savings. Bordalo, Gennaioli and Shleifer (2022) discuss the role of salience and reminders in decision-making, and how reminders about infrequent events are likely to be more powerful than generic reminders. More in general, as Verhoogen (2021) points out, evidence of non-profit maximizing behavior is largely lacking beyond the agricultural sector, a gap that this paper fills by focusing on small but relatively sophisticated firms that operate online businesses. Moreover, this study combines novel administrative data from the e-commerce industry with a field experiment involving a large number of firms, which represent rare features in the literature.

2 Context

E-commerce has become a leading sector in emerging markets, especially since the COVID-19 pandemic, offering opportunities for economic inclusion, innovation, and growth (World Bank, 2022, 2023). In this section, I describe the context in which the experiment took place, focusing on characterizing the sample of participating firms and the importance of Black Friday as a business opportunity in the e-commerce sector and beyond.

2.1 Sample

The experiment was conducted in advance of Black Friday 2021, in collaboration with one of the largest platforms for e-commerce in Latin America (henceforth, the platform).

The platform is a B2B company that provides web-hosting services for firms that wish to sell online, akin to Shopify in the US/Europe. Crucially, it is not an *aggregator* or online marketplace —such as eBay or Mercado Libre—, as each firm operates from their own URL (e.g., www.myfirm.com). This has important implications for firm strategy and market dynamics, as each firm must attract clients and gain reputation on an individual basis, 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 are automatically integrated with payment and delivery services, and social media pages and other tools for web analytics and search engine optimization (SEO) are very easy to integrate. There is also a myriad of third-party apps available that can be linked to the website, ranging from accounting and inventory management programs to chat bots and customer retention tools. The platform charges a two-part tariff composed of a fixed monthly fee plus a variable rate per sale ranging from 0.5% to 2%. The platform provides a low entry cost alternative to start selling online, which results in having a client base largely composed of small firms.

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 the platform classified as "tiny" and "small" at the time.[3] This resulted in a total 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 average sales of $ 545 per month during the three months leading

[3]The platform classifies firms to be "tiny" if they have between 7 and 30 transactions in the last 90 days and "small" if they have between 31 and 150 in the same period.

up to the intervention.[4] Moreover, 91% of the sample has at most 5 full time employees (microfirms) and 50% has no brick-and-mortar stores (fully online operations), although these are self-reported and are available for 56% and 65% of the firms, respectively. The reporting is done by the manager of the online store, who is usually also the owner of the firm or a close relative (*e.g.*, a tech savvy child), per conversations with platform officials. Only in a small share of cases it is a hired employee. However, I do not observe this information in the data.

Managers can also report the industry of the firm. 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.

Finally, 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, managers integrate on average 4.43 apps to the online store (or 2.47 excluding basic apps, such as the platform's iOS or Android ones). Figure A1 shows the list of most commonly used third-party apps in each country, with logistics being the most popular category in both cases.

2.2 Black Friday

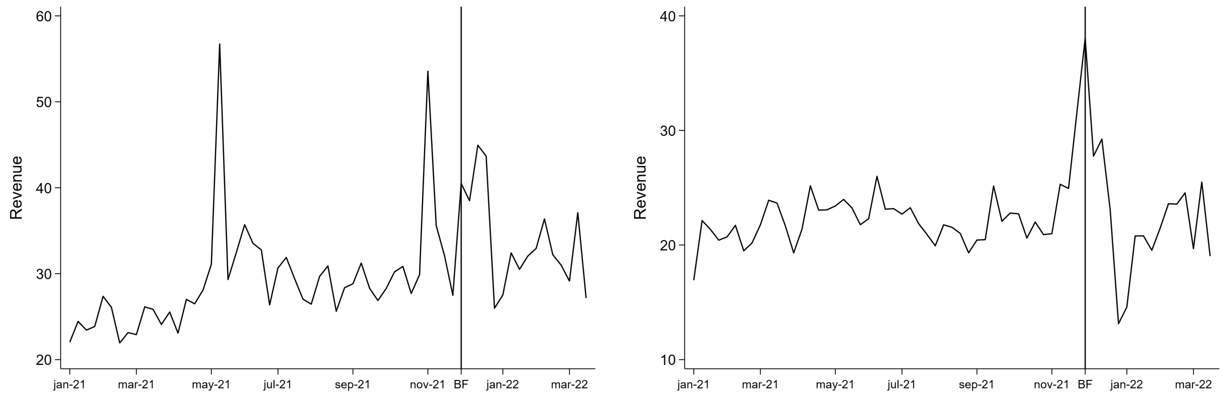
The experiment leverages Black Friday as an opportunity for online retailers to increase their sales and to expand their client base. The tradition of having large sales events on the Friday after Thanksgiving is said to have started in Philadelphia (US) in the 1960s, turning especially popular since 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 began in Argentina and Brazil in 2013 and 2010, respectively.

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.

However, there are significant differences between Argentina and Brazil. The latter fol-

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

Figure 1: Weekly revenue during sampled period



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

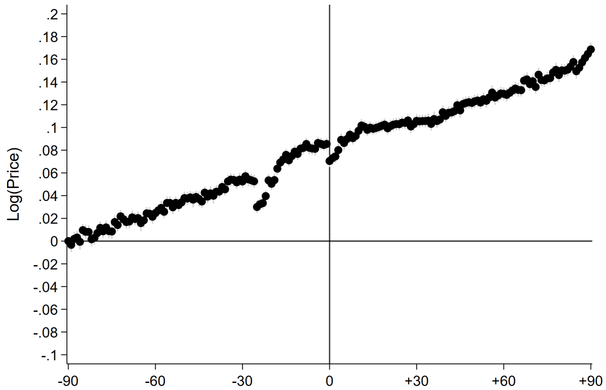
Note: This figure presents the evolution of weekly revenue among sampled firms. Argentina presents two major spikes during 2021 before the occurrence of Black Friday: the Hot Sale in May and Cyber Monday in October. Brazil has one spike during 2021, on the week that combines Black Friday with Cyber Monday (they do not hold the Hot Sale event).

lows the US practice of combining Black Friday with Cyber Monday three days later, which is another sales event focused on e-commerce. Argentina, instead, holds Cyber Monday about four weeks before BF, making BF a significantly smaller event for online retailers. This is observed in Figure 1, which plots the evolution of weekly revenue between January 2021 and March 2022 among firms in the sample, separating by country. This important difference makes BF a more salient event in Brazil than in Argentina.

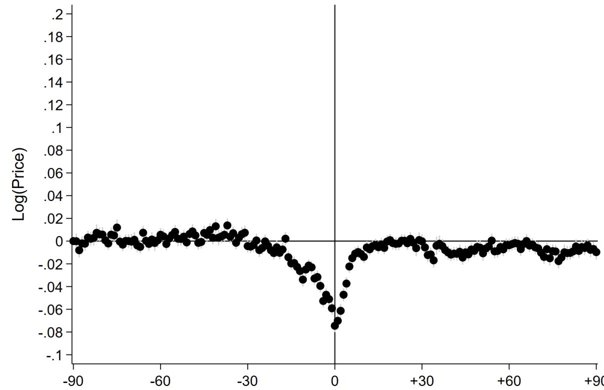
A question that consumers often wonder about is whether discounts are real during major sales events. That is, to what extent products are actually discounted compared to their normal price. Figure 2 presents the price evolution of transacted products during 90 days before/after BF, controlling for product fixed effects. Price reductions are, on average, small: roughly 1.5% in Argentina and 7% in Brazil. Note, however, that these data cover all products, including those that were not offered at a discount. These graphs also reflect the higher importance that BF has in Brazil compared to Argentina. In the latter country, discounts are larger on Cyber Monday, while in the former this happens the day of BF.

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). Given the importance of the event, we may expect behavioral frictions to be relatively less prevalent compared to day-to-day operations.

Figure 2: Daily evolution of prices around Black Friday



(a) Argentina



(b) Brazil

Note: This figure presents event study coefficients where the outcome variable is log-transformed prices (based on transactions). Each coefficient corresponds to a day before/after Black Friday (period 0). The coefficient for period -90 is normalized to zero. Argentina's plot presents two peculiarities: a linear increase in prices over time, which reflects the inflationary process the country was going through, and a fall in prices roughly four weeks before BF, which reflects the Cyber Monday event, that takes place before BF instead of on the following Monday as in the US or Brazil.

3 Methods

This section describes the data collected for the paper, the design of the experiment, and the regression models to be estimated in the Results sections.

3.1 Data

The platform provided data on online operations and firm characteristics. These data include sales at the product level and the firm level between January 1, 2021 and March 15, 2022. Product-level data include daily quantities sold and revenue, while firm-level data include daily revenue, discounts, and shipping costs. The platform also extracted the full list of products posted on the store including price and available stock as of November 25, November 26 (Black Friday), November 29, and December 6, 2021, and the set of firm characteristics included in Table A1.

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).

3.2 Experimental Design

The experiment consisted of the distribution of messages to the managers of online stores. Firms were randomly split into a treatment and a pure control group. Specifically, treatment group managers received messages nudging them to engage with BF. They received the same message twice, which consisted of the following text:

> *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 subject line read: "*Grow your sales and win an iPad!*"

The message is designed to nudge managers to plan their pricing and advertising strategies for BF by attracting attention to the event. 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 168 managers submitted their flyer (1.74% of treated firms). Moreover, the message 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!*" Given these features, including the reminder and the salient language, the nudge may help to alleviate attention or memory constraints.

An alternative interpretation is that the message is actually providing information, as opposed to addressing behavioral constraints. If managers are not aware of the existence of Black Friday or of its importance, this message may update their information sets, leading them to change behavior through the traditionally rational channel. There are various reasons to think this is not the case. Section 4.4 provides evidence that the intervention did not affect engagement with the event, making it implausible that managers were unaware of its existence. This is also confirmed anecdotally by talking to online store managers and by platform officials. Additionally, Section 4.5 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 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). The number of strata is 112.

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 in the bottom-right corner of the screen when the manager logs into the online store.[5] All communications were distributed by the platform, who regularly sends messages through these channels. Open rates by the start of BF 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.

3.3 Empirical Model

I estimate intent-to-treat (ITT) effects throughout the paper, relying on treatment randomization as a source of identification. I obtain dynamic treatment effects when pre- and post-treatment data are available by estimating event-study models of the following form.

$$y_{it} = \alpha_i + \gamma_t + \sum_{m=-G}^{M} \beta_m z_{i,t-m} + \epsilon_{it} \tag{1}$$

Where y_{it} is an outcome of interest for firm i on period t, α_i is a firm fixed effect, and γ_t is a time fixed effect. The regressors of interest, $z_{i,t-m}$, 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

[5] During the second round of communications, Argentine firms received another message by mistake, which included the nudge plus a description of the loss-leader strategy for setting discounts (Hess and Gerstner, 1987). This second message was distributed among a group of stores not included in the present sample and had a null impact on performance (Figure A6). Thus, if anything, Argentine firms should suffer from downward bias. Moreover, as Brazilian firms were not affected, I replicate the analysis only on them in the Appendix, finding that all main results of the paper are noisier but similar in nature.

out of the intervention. The vector β captures the dynamic treatment effects with respect to a baseline period, which I set to the one right before the onset of the experiment. Standard errors are clustered at the firm level throughout the paper under this model.

Some regressions only involve a cross-sectional analysis, in which case I estimate the following model.

$$y_i^d = \alpha + \beta z_i + \delta_{s(i)} + \epsilon_i \tag{2}$$

Where z_i is an indicator for being assigned to treatment and $\delta_{s(i)}$ is a vector of strata fixed effects (Bruhn and McKenzie, 2009).

3.4 Balance check

Table 1 presents a check that randomization was successful. I regress the treatment group indicator 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, with and without controlling for strata fixed effects. Baseline characteristics include the log of revenue between August and October 2021; months since entry; indicators for having different possible numbers of employees (and whether the firm reports it); the analogous for number of brick-and-mortar stores; indicators for having Instagram or Facebook pages linked to the online store; and indicators for having integrated Google Analytics.

Table 1: Balance table

	Treated	
	(1)	(2)
Log(Sales Aug-Oct '21)	0.001	0.007
	(0.004)	(0.007)
Months since entry	0.000	0.000
	(0.000)	(0.000)
0-1 employees	-0.060	-0.063
	(0.056)	(0.057)
2-5 employees	-0.060	-0.063
	(0.056)	(0.057)
6-25 employees	-0.039	-0.040
	(0.060)	(0.061)
Reports employees	0.047	0.049
	(0.056)	(0.058)
0 B&M	0.012	0.011
	(0.086)	(0.087)
Showroom only	0.001	0.000
	(0.087)	(0.088)
1 B&M	0.034	0.034
	(0.086)	(0.087)
2-5 B&M	0.014	0.013
	(0.088)	(0.089)
Reports B&M	-0.016	-0.019
	(0.086)	(0.088)
Instagram	-0.001	-0.002
	(0.025)	(0.026)
Facebook	-0.007	-0.007
	(0.013)	(0.013)
Google analytics	-0.004	0.034
	(0.011)	(0.031)
Integrated apps	0.003	0.005**
	(0.002)	(0.002)
Strata FE	No	Yes
Control mean	0.50	0.50
F-test p-value	0.82	0.53
Obs.	9664	9664

Note: Column 1 regresses an indicator for being in the treatment group on a set of baseline characteristics. Column 2 additionally controls for strata FE. The p-value associated to the F test of joint significance is 0.82 and 0.53 in each respective column.

4 Results

This section presents the results of the paper. First, it demonstrates that planning resulted in higher revenue for treated firms. Second, turning to mechanisms, it provides evidence that the nudge effectively led managers to plan in advance for the event, both through targeted and non-targeted behavior. In particular, while the messages did not affect pricing decisions, they led to more effective advertising and inventory management.

4.1 Revenue

In this section, I present the impact of the intervention on the revenue of online stores, estimating equation 1 under different specifications. Results indicate that messages led to a roughly 4% increase in revenue for 20 to 60 days post-intervention, driven by an increase in quantities sold and robust to alternative specifications.

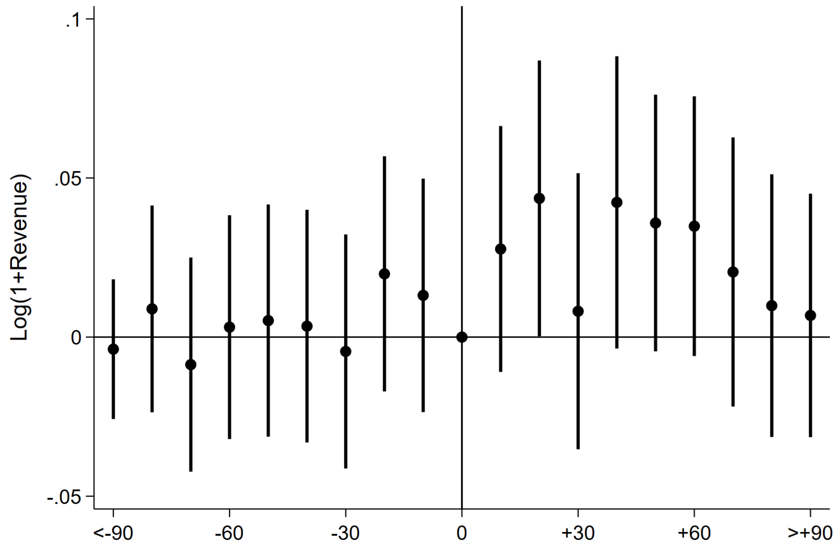
Figure 3 plots the coefficients obtained on log-transformed revenue. It shows an average increase of 3.6% in the first 20 days after the onset of the intervention, fading away from there on and fully disappearing after 60 days, averaging a total of 3.2% throughout that period. Reassuringly, there are no significant pre-trends, which would have posed a threat to identification. There is also no evidence of a long-lived effect, as the last coefficient in the event study stabilizes around zero.

In the Appendix, Figure A2 shows that effects are robust to an alternative specification, using revenue as the outcome variable and trimming the sample at the top 1% of the distribution to account for outliers. This approach addresses concerns around the $log(1 + x)$ transformation, raised recently by Chen and Roth (2023). The dynamics of the effect are similar, in this case averaging an increase of \$ 0.93 per day in the first 20 days (4.4%) and of \$ 0.79 over the 60 days post-intervention (3.9%).

We can decompose revenue into prices and quantities to proxy for the evolution of profits. If revenue is going up at the expense of falling prices it could be a signal of falling profits.[6] However, Figures A3 and A4 show that the increase in revenue is explained by an increase in quantities, with prices remaining similar across treatment and control firms, especially in the first 20 days post-intervention. Importantly, to the extent that marginal costs were unaffected by treatment, this would indicate an increase in profits at a similar rate than revenue.

[6] Although section 4.4 shows that listed prices are not affected by the nudge, sales could be driven only by products offered at heavy discounts.

Figure 3: Log(1+revenue)



Note: The outcome variable is the log-transformed value of daily revenue plus 1. Time period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. Plotted coefficients reflect intent-to-treat effects. 95% confidence intervals. Standard errors clustered at firm level.

Taken together, these findings reveal a significant positive effect on firm performance, mainly in the period between the few days before BF and the week after the event. Alternatively, the lack of end-line effects implies that the intervention does not reduce firm exit. In the next sections I leverage the richness of the data to analyze different factors that may have contributed to this baseline result.

4.2 Advertising

The experiment aimed to engage managers with planning in advance of BF. Moreover, it targeted a specific business practice: advertising. This section leverages unique data on Instagram posting activity to analyze the impact of the intervention on advertising behavior. Results show that the nudge increased the probability that managers advertise discounts during the week before BF, which is consistent with enhanced managerial planning.

Advertising is a fundamental aspect of firms' operations. Business training programs for entrepreneurs typically include a module on this topic, such as the International Labour Organization's Start-and-Improve Your Business program (De Mel, McKenzie and Woodruff, 2014) or those programs implemented in Anderson and McKenzie (2022) and Jin and Sun (2024). Moreover, McKenzie and Woodruff (2017) observe that small firms in less developed countries tend to struggle in this area, as only 17% of sampled firms implement some form of advertising—despite their finding that marketing practices is one of the two sets of practices most strongly associated with firm performance, together with record keeping.

Advertising is especially relevant for online businesses like those in this paper, that operate from their own websites and not through a centralized marketplace, such as Amazon or eBay. Their usual approach is to focus their efforts on social media advertising, especially Facebook and Instagram, which offer a potentially large amount of traffic and allow free advertising in the form of posts. Indeed, 72% of firms in the sample have a Facebook account and 95% have an Instagram account. Firms can also pay for ads on social media, Google, or other channels, but it is less common among smaller firms such as those in this paper.

Leveraging data on Instagram activity, I find no evidence that the nudge affected the total amount of posts but I do observe a substitution of generic advertising with advertising discounts. The former result is presented in Figure A5, which shows that the likelihood of posting content on Instagram did not change after the intervention. This may be a consequence of firms already following an optimal strategy on this front. Moreover, they tend to be very active: the probability of posting at least once on any given day during the sample period is 29% and the average number of posts per day is 0.46.

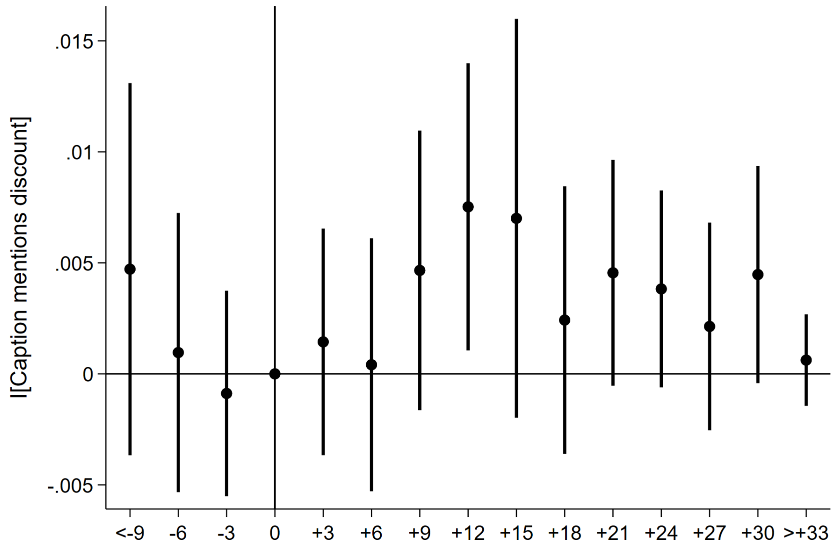
Alternatively, Figure 4 presents the effects of the nudge on the likelihood of advertising discounts. Specifically, the outcome variable is an indicator for mentioning terms related to Black Friday or discounts in the caption of the post. We observe that firms assigned to receiving the nudge display a higher likelihood of around 0.0075 percentage points (pp) at its peak, which occurs between 9 and 12 days after the onset of the intervention. This represents a 16.2% increase over the control group mean during that period.

Reassuringly, we don't observe statistically significant differences between treatment and control before the experiment. We also observe a null effect in the medium run, as the last coefficient—which incorporates all observations between 30 and 120 days after the experiment—is virtually equal to zero. Interestingly, we observe an almost significant difference around December 10-12, which may indicate short-term learning that led to more discount advertising in advance of Christmas.

4.3 Inventory management

Do managers only react along the lines of what they are told, or is there room for broader-than-anticipated effects on behavior arising from the nudge? This section shows that managers also improve their inventory management in advance of the event, which is an important

Figure 4: Advertising discounts on Instagram



Note: The outcome variable is an indicator taking value 1 if the firm posts on Instagram and mentions discounts at least once in the day. Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 3-day bins. Period 0 corresponds to the three days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

business practice that was not targeted by the nudge. Inventory management plays a key role in a firm's operation, with multiple papers documenting its importance among small firms in less developed contexts (Kremer et al., 2013; Bloom et al., 2013; McKenzie and Woodruff, 2017). Moreover, in the presence of a major sales event such as Black Friday, insufficient inventory can be a major cause for underperformance if firms run out of stock.

Leveraging data on product listings as of the day before BF, Table 2 shows that nudged firms have a higher number of products listed (7.2%), a higher number of products with positive stock (6.3%), and a higher number of products with a large amount of stock—100 units or more (10.9%).[7] These results are consistent with enhanced planning: managers who received the nudge were more likely to update their product listings in time for the event and to increase stock availability.

[7] Managers have strong incentives to keep inventories updated on the platform: if a product runs out of stock, customers will see a corresponding sign in the online store and will not be able to make a purchase.

Table 2: Inventory management

	log(products)	log(products) | stock>0	log(products) | stock>100
	(1)	(2)	(3)
Nudge	0.07**	0.06**	0.11*
	(0.03)	(0.03)	(0.06)
Strata FE	Yes	Yes	Yes
Control mean	5.58	5.59	5.80
Obs.	9660	9633	5881

Note: Column 1 regresses the log of number of products listed as of the day before Black Friday (BF). Columns 2 and 3 regress the the analogous considering only products with positive stock and with more than 100 units in stock, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

This unexpected finding—inventory management was not a targeted practice in the intervention—implies that the nudge induced a holistic reaction. This is consistent with behaviorally (and not informationally) constrained managers, since the messages contained no information related to inventory management; only a nudge promoting planning. Moreover, this result is in line with recent lab experimental work showing that nudges can improve non-targeted but complementary behaviors (Altmann, Grunewald and Radbruch, 2024).

4.4 Pricing

Leveraging data on firms' full product listings on the day of BF, Table A2 presents the effects of the nudge on different measures of pricing, based on Equation 2. These data improve upon the transactions data by allowing to evaluate the impact of the nudge on the prices of all products offered by firms, disregarding whether consumers demanded them or not.

Results show small and statistically insignificant effects on the probability of discounting at least one product as well as on average prices, using both the full listing of products and the top 5 products only, based on quantities sold in the pre-intervention period. These results imply that the nudge did not affect engagement with BF, which is in line with the importance of the event in the e-commerce industry described in section 2.2. Indeed, 73% of firms in the sample offer at least one discount that day. This result is also reassuring that the nudge did not provide novel information to store managers, as there is no evidence that receiving the nudge increased participation in the event.

4.5 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. The analysis builds on a machine learning methodology that predicts conditional average treatment effects (CATE) for each firm, applying a causal forest estimation (Athey, Tibshirani and Wager, 2019). Previous papers have implemented this methodology and provide useful discussions on how to do it. See, for example, Carlana, La Ferrara and Pinotti (2022) and Barboni, Cárdenas and de Roux (2022).

The analysis focuses on the effect of the nudge on revenue during the 20 days after the onset of the intervention, which is when baseline effects are statistically and economically stronger. I feed the algorithm with all available information on firm characteristics and predict treatment effects at the firm level based on those characteristics. A key advantage of this approach is that it incorporates all available information, saving the researcher from making the discretionary choice of what covariates to focus on.

Table 3 presents the results. Specifically, I test whether firm characteristics are different across the groups with CATE below or above the median CATE. Column 3 shows the differences in the mean value of each characteristic between firms from each group, and column 4 provides the corresponding p-value adjusting for multiple hypothesis testing based on List, Shaikh and Xu (2019).

We observe a robust set of results, indicating that the nudge had a stronger effect on relatively larger firms, including those with higher pre-treatment revenue, older, with more employees, and with a venue to display the products (a showroom or a brick-and-mortar store). Perhaps counter-intuitively, more developed firms benefit more from a simple behavioral intervention such as the nudge presented in this study. Moreover, results also show that the effect was stronger among firms more likely to use social media and search engine optimization tools, such as Google Analytics. Taken together, these results are consistent with a strategic complementarity between nudges and pre-established firm capabilities. In particular, firms that are too small may lack the necessary ability or infrastructure to react effectively to the nudge, missing out on the opportunity to increase sales around the event.

Finally, Argentine firms are significantly more likely than Brazilian firms to belong in the upper half of the CATE distribution. Although multiple market characteristics could account for this result, a crucial difference between the two countries is the salience of Black Friday in each case, as discussed in Section 2.2. In particular, BF is the main sales event in the year in Brazil, while it is much smaller in Argentina (where Cyber Monday and the

Hot Sale are the larger ones). This implies that Argentine managers are likely to be less attentive to BF than Brazilian ones, reinforcing the interpretation that the nudge operates by addressing limited memory or limited attention.

Table 3: Heterogeneous treatment effects on revenue

Variable	(1) Low Predicted TE	(2) High Predicted TE	(3) Diff.	(4) MHT p-value
Pre-treatment revenue (logs)	2.308	2.932	0.624***	0.001
Firm age (months)	16.527	29.310	12.783***	0.001
Employees: 0-1	0.317	0.307	-0.009	0.951
Employees: 2-5	0.207	0.200	-0.007	0.974
Employees: 6-25	0.022	0.053	0.031***	0.001
Employees: 25+	0.008	0.012	0.005	0.273
Employees: N/A	0.446	0.427	-0.019	0.502
Brick & Mortars: 0	0.387	0.260	-0.126***	0.001
Brick & Mortars: showroom	0.070	0.124	0.054***	0.001
Brick & Mortars: 1	0.143	0.229	0.086***	0.001
Brick & Mortars: 2-5	0.027	0.043	0.016***	0.001
Brick & Mortars: 5+	0.003	0.005	0.001	0.938
Brick & Mortars: N/A	0.370	0.339	-0.031**	0.024
Ind: Clothing	0.299	0.395	0.096***	0.001
Ind: Home & Garden	0.046	0.056	0.010	0.301
Ind: Health & Beauty	0.056	0.042	-0.015**	0.028
Ind: Food & Drinks	0.033	0.031	-0.002	0.999
Ind: Art & Antiques	0.039	0.024	-0.015***	0.001
Ind: Gifts	0.025	0.030	0.005	0.716
Ind: Jewelry	0.025	0.026	0.001	1.000
Ind: Books	0.019	0.019	0.000	0.999
Ind: Toys	0.018	0.013	-0.005	0.506
Ind: Electronics	0.010	0.013	0.003	0.910
Ind: Sports	0.012	0.013	0.001	0.999
Ind: Other	0.102	0.117	0.015	0.261
Ind: N/A	0.316	0.221	-0.094***	0.001
Apps integrated	4.683	4.142	-0.541***	0.001
Instagram account	0.954	0.953	-0.001	0.997
Facebook account	0.674	0.775	0.101***	0.001
Google Analytics	0.386	0.421	0.035***	0.001
Country: Argentina	0.462	0.598	0.136***	0.001
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 20 days after the intervention. CATEs are obtained through a causal forest estimation, 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). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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 purely behavioral treatments can improve business practices and firm performance.

This paper presents the results of an experiment with a large sample of Argentine and Brazilian firms, testing whether a simple intervention in the form of messages sent to managers of small e-commerce businesses can improve firm performance around a major business opportunity. The main result shows that nudging managers to plan resulted in approximately 4% higher revenue over a period of 20 to 60 days. Evidence on mechanisms is consistent with treated managers implementing more effective advertising and inventory management. Importantly, larger and more sophisticated firms benefited the most from the intervention, suggesting that pre-established capabilities may complement this type of interventions.

Policymakers aiming to support small firms, especially in developing economies, may consider helping managers and entrepreneurs with attention and memory frictions through their programs. Simple, cost-effective nudges can offer a way to enhance business practices for relatively short periods of time, opening windows of opportunity when properly timed around important events. However, the effectiveness of such interventions can be contingent on the existing capabilities of firms, suggesting that alleviating constraints among entrepreneurs who are most in need of help may require more involved and tailored solutions.

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Appendix

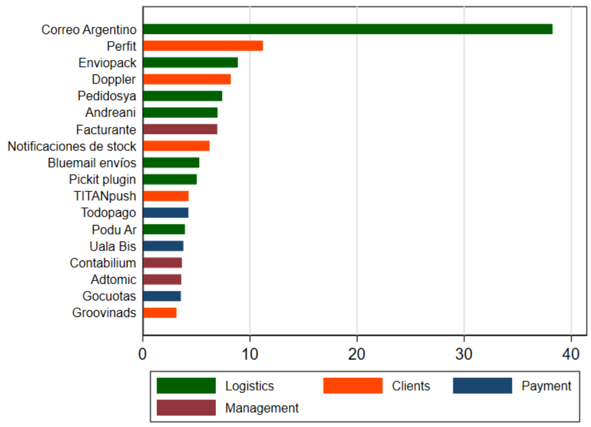
Context

Table A1: Sample characteristics

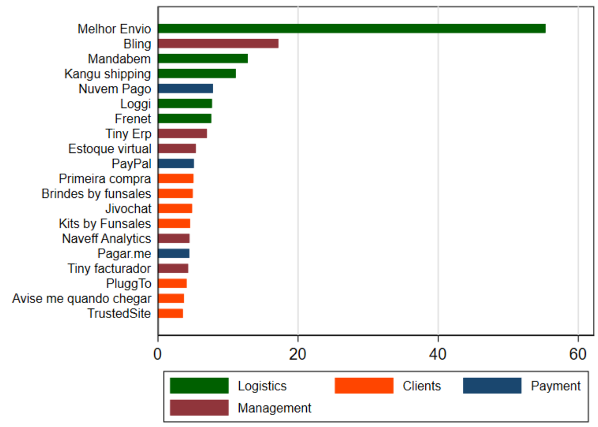
	count	mean	sd	min	max
Sales Aug-Oct ’21	14494	1633.95	4106.39	0	319904
Months since entry	14494	22.96	19.79	1	122
Microfirm	8168	0.91	0.29	0	1
Online only	9372	0.50	0.50	0	1
Ind: Clothing	10601	0.51	0.50	0	1
Ind: Home & Garden	10601	0.07	0.25	0	1
Ind: Health & Beauty	10601	0.07	0.25	0	1
Ind: Food & Drinks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

This table presents summary statistics for the main covariates observed in the data. *Sales Aug-Oct ’21* include total revenue in USD 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. *Instagram* and *Facebook* are indicators for having Instagram or Facebook accounts linked to the store. *Google analytics* is an indicator for having activated such tool on the store. *Integrated apps* is the total number of third-party apps integrated to the store.

Figure A1: Frequency of third-party apps



(a) Argentina

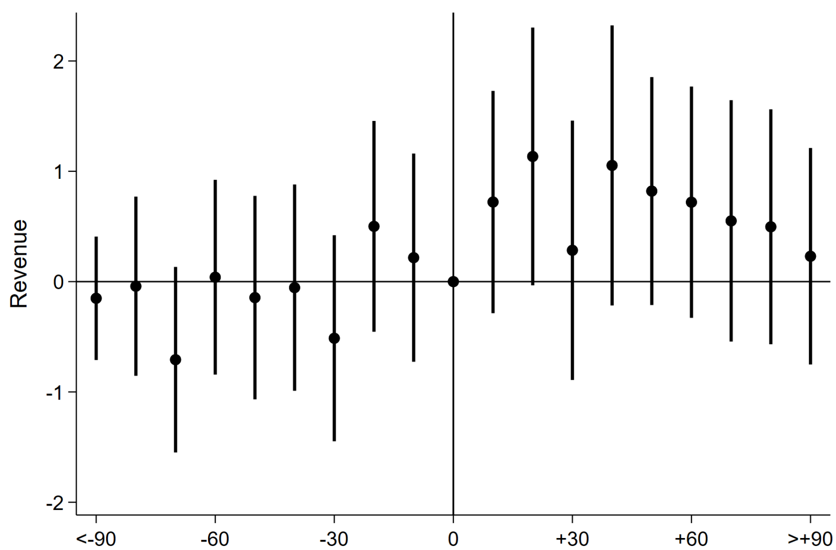


(b) Brazil

Note: This figure presents the prevalence of each of the 20 most popular apps in the stores from each country.

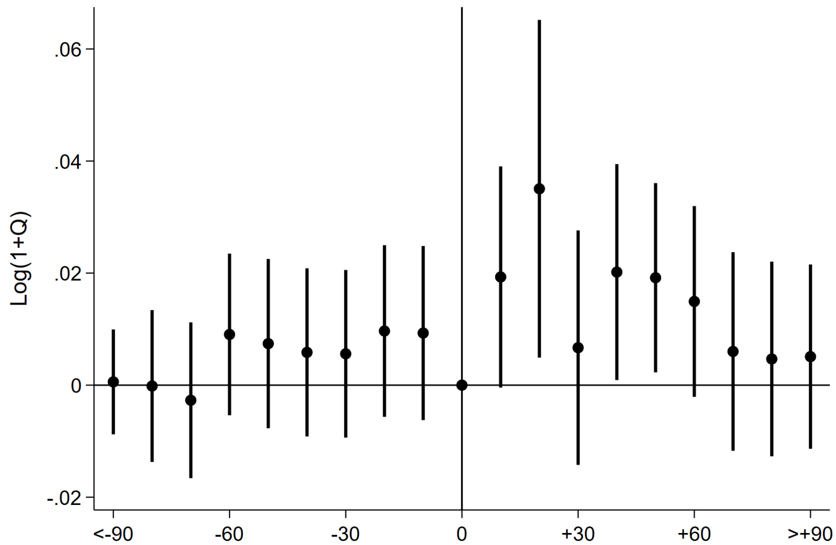
Additional results on revenue

Figure A2: Revenue (trimmed top 1%)



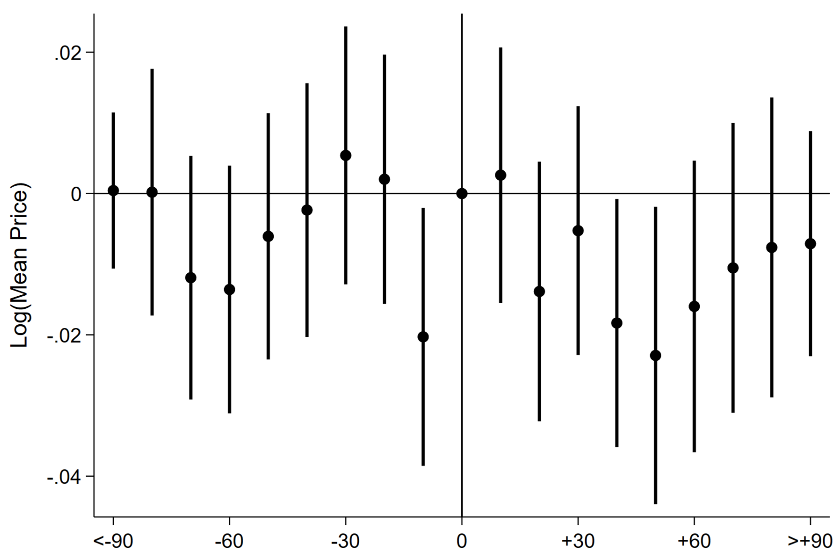
Note: The outcome variable is daily revenue, trimmed at the top 1%. Time period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. Plotted coefficients reflect intent-to-treat effects. 95% confidence intervals. Standard errors clustered at firm level.

Figure A3: Quantities sold



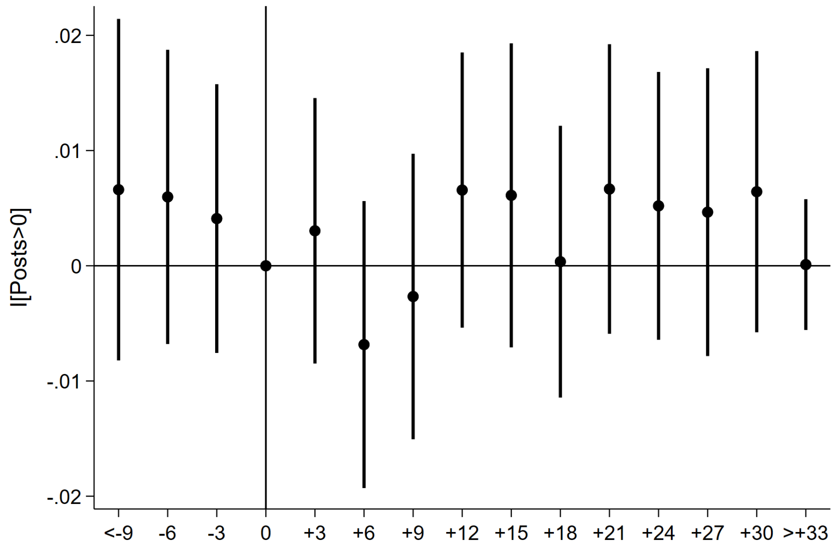
Note: The outcome variable is the log of 1 plus product quantities sold per day. Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Figure A4: Average price



Note: The outcome variable is the log of 1 plus revenue over quantities sold (average daily price). Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Figure A5: Posting activity on Instagram



Note: The outcome variable is an indicator taking value 1 if the firm posted on Instagram at least once in the day. Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 3-day bins. Period 0 corresponds to the three days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

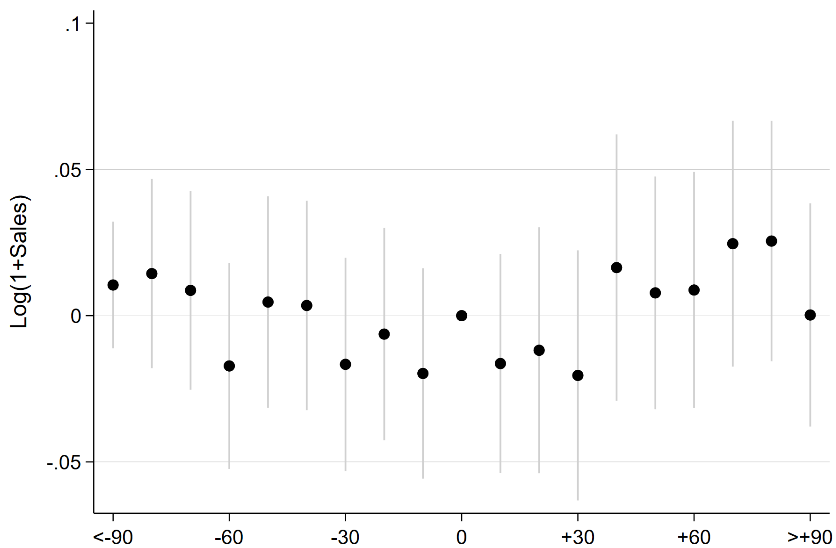
Additional results on pricing

Table A2: Pricing

	Full listing		Top 5 products	
	(1)	(2)	(3)	(4)
	Any disc.	Log(Avg. Price)	Any disc.	Log(Avg. Price)
Nudge	0.014	-0.003	0.012	0.006
	(0.009)	(0.020)	(0.009)	(0.025)
Strata FE	Yes	Yes	Yes	Yes
Control mean	0.725	6.264	0.298	5.899
Obs.	9664	9634	9664	8299

Note: Measures of pricing on the day of BF. Columns 1–2 consider all products and columns 3–4 consider the five most sold products only, based on pre-treatment quantities sold. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

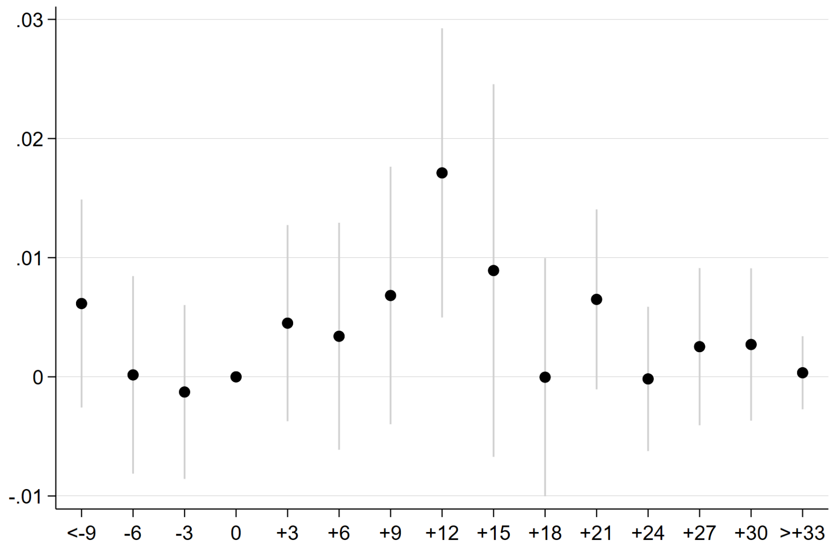
Figure A6: Log(1+revenue), alternative message



Note: This figure shows the treatment effect of the alternative message that Argentine firms received during the second round of communications, on top of the planned message (the nudge). The estimating sample is a group of firms that received only this message (not considered in the rest of the paper) and the control group firms from this paper. The plot shows a null impact of this message on performance, implying that Argentine firms in the main sample may suffer, if anything, from downward bias. The outcome variable is the log-transformed value of daily revenue plus 1. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Replication under Brazilian sample only

Figure A7: Brazil only: Advertising discounts on Instagram



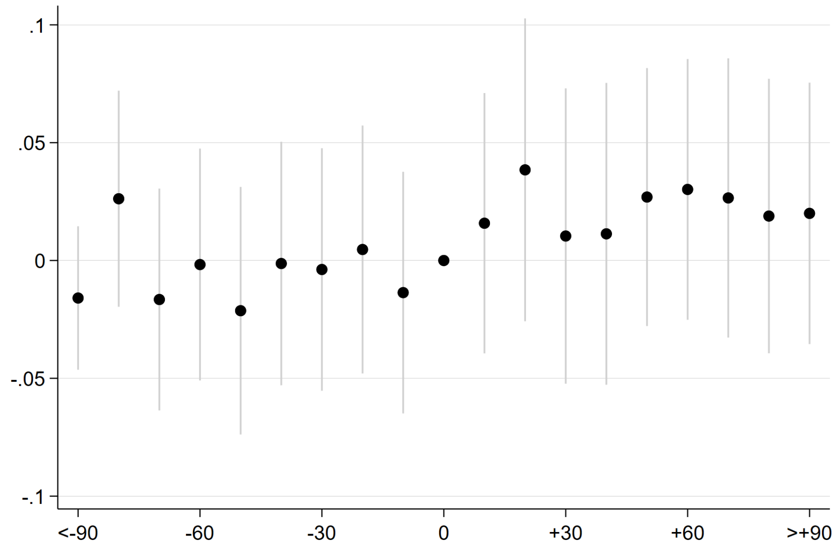
Note: Brazilian firms only. The outcome variable is an indicator taking value 1 if the firm posts on Instagram and mentions discounts at least once in the day. Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 3-day bins. Period 0 corresponds to the three days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Table A3: Brazil only: Inventory management

	log(products)	log(products) | stock>0	log(products) | stock>100
	(1)	(2)	(3)
Nudge	0.10**	0.10**	0.19*
	(0.04)	(0.04)	(0.10)
Strata FE	Yes	Yes	Yes
Control mean	5.59	5.59	5.86
Obs.	4545	4529	2666

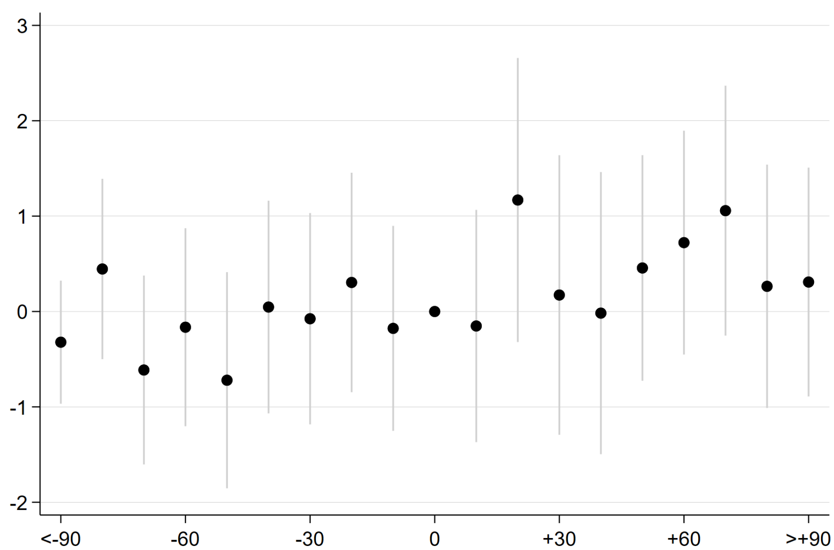
Note: Brazilian firms only. Column 1 regresses the log of number of products listed as of the day before Black Friday (BF). Columns 2 and 3 regress the the analogous considering only products with positive stock and with more than 100 units in stock, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A8: Brazil only: Log(1+revenue)



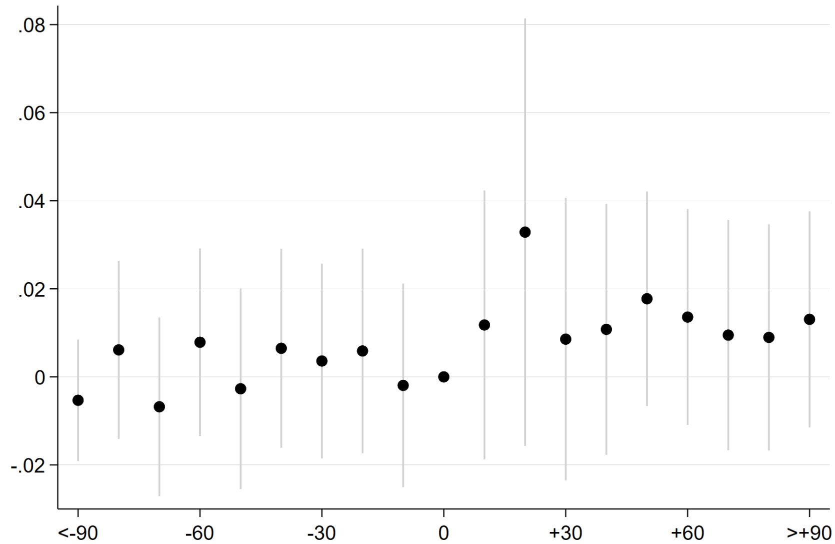
Note: Brazilian firms only. The outcome variable is the log-transformed value of daily revenue plus 1. Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Figure A9: Brazil only: Revenue (trimmed top 1%)



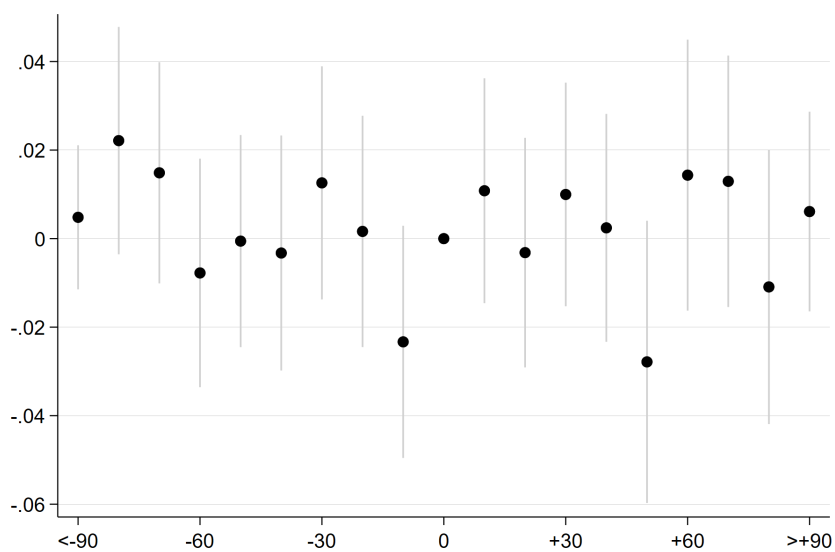
Note: Brazilian firms only. The outcome variable is revenue, trimmed at the top 1%. Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Figure A10: Brazil only: Quantities sold



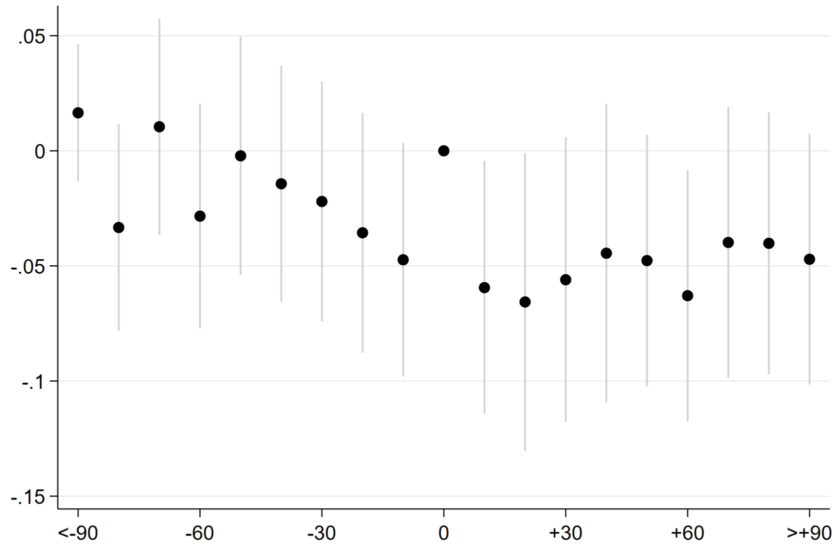
Note: Brazilian firms only. The outcome variable is the log of 1 plus product quantities sold per day. Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Figure A11: Brazil only: Average price



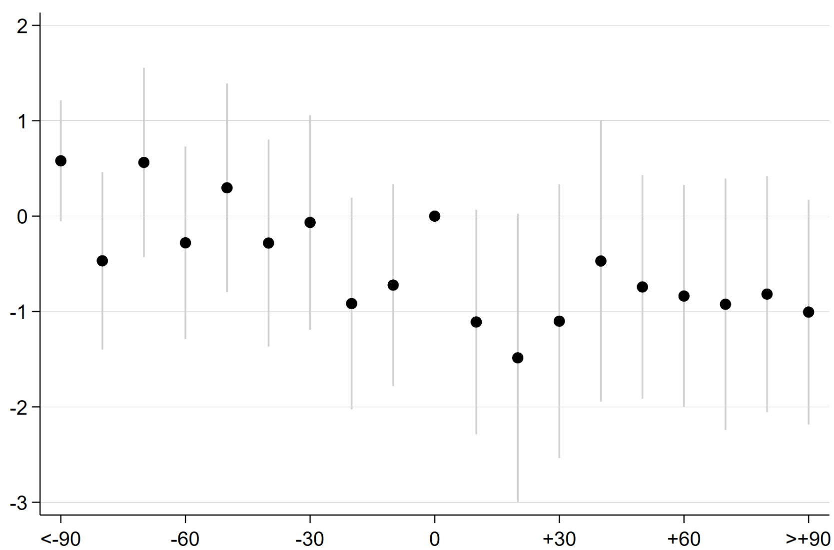
Note: Brazilian firms only. The outcome variable is the log of 1 plus revenue over quantities sold (average daily price). Plotted coefficients correspond to intent-to-treat effects. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Figure A12: Brazil only: Log(1+revenue)



Note: Brazilian firms only. The outcome variable is the log-transformed value of daily revenue plus 1. Plotted coefficients correspond to the information treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.

Figure A13: Brazil only: Revenue (trimmed top 1%)



Note: Brazilian firms only. The outcome variable is revenue, trimmed at the top 1%. Plotted coefficients correspond to the information treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered at firm level.