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 14,500 small e-commerce firms in Argentina and Brazil, which consisted of randomizing messages that encouraged managers to plan their pricing and advertising strategies for Black Friday, a major sales event. 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. Additional evidence suggests that the nudge helped managers overcome procrastination. Finally, the effects are stronger among relatively larger firms that use search engine optimization (SEO) tools, suggesting that pre-established capabilities are important for reaping the benefits of the intervention.

JEL Codes: D22, D91, L25, M11, M31
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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 practices significantly influence firm productivity (Bloom and Van Reenen, 2007, 2010). 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 14,494 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 tied to a deadline: 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 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%), without increasing the number of posts. Additionally, these firms exhibited a 6-11% increase in the number of products listed as in stock.

Planning was fruitful. Treated firms display 3.5%-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 sales into prices and quantities reveals that the increase is driven

[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).

by the latter, suggesting that profits increased at a similar rate than revenue. All estimates correspond to intent-to-treat effects, where 72% of managers read the message at 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).

I also employ machine learning methods to uncover heterogeneities in the nudge's 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). I find that the nudge had stronger effects on larger firms, particularly those with higher pre-treatment sales, those that are older, and those more likely to have physical stores. Additionally, firms using Search Engine Optimization (SEO) tools, such as Google Analytics, also experienced more pronounced effects. These results suggest that pre-existing firm and managerial capabilities are crucial for effectively reacting to the nudge and reaping its benefits.

Why did the nudge affect behavior? I argue that the evidence is broadly consistent with having helped managers overcome procrastination. Firstly, there is no evidence that the intervention affected pricing dynamics, suggesting that managers were already aware of Black Friday's existence and its approaching occurrence. Therefore, the nudge did not alleviate any informational frictions in this regard. Secondly, the raffle did not alter the incentive structure for managers, as the expected monetary value of participation was only $0.12. Indeed, participation was minimal: fewer than 2% of managers submitted a flyer, despite 35% of them advertising discounts on social media between the intervention and BF. Lastly, the language used in the message provided cues to initiate planning and made salient the costs associated with delaying action, which could potentially help managers overcome present bias (Akerlof, 1991; O'Donoghue and Rabin, 1999).

Finally, the experiment also included a second treatment arm, in which managers received both the nudge and information on a challenging issue for this type of firms: the pricing strategy. Specifically, they were provided with an explanation of the loss-leader approach, which involves heavily discounting one or a few products to attract customers and boost sales of other, more profitable items (Hess and Gerstner, 1987). However, this additional information did not influence pricing decisions, including the adoption of the loss-leader approach, suggesting that informational constraints were weaker than anticipated. The information treatment also had no effect on advertising and only a mild, imprecisely estimated negative impact on inventories. Despite this, firms in this group performed significantly worse than those in the first treatment arm, which received only the nudge. Moreover, the sales trajectory under the second treatment arm was economically and statistically similar to that of the control group, indicating that the information undermined the benefits of the nudge. Analyzing participation rates in the raffle, I find that managers in the second treatment group were significantly less likely to participate than those in the nudge-only group (-29%). This pattern is consistent with information overload, where the explanation of the loss-leader approach crowded out managers' engagement with the nudge. These findings complement the first set of results of the paper, illustrating from different angles how behavioral frictions can be an important determinant of managerial practices and the performance of small firms.

This paper makes the following contributions. First, it presents 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 an important 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), as well as to recent work studying "behavioral firms," which has mainly 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 recent work by Gertler et al. (2023), who show that distrust can prevent small Mexican firms from accepting a service fee reduction, while procrastination does not play a role. My paper shows evidence consistent with procrastination being an important barrier to adopting profitable opportunities when the action (planning) involves a higher immediate cost. 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 sophisticated firms running online businesses. Moreover, my work leverages novel data on the e-commerce industry and a field experiment with a large number of firms, which are rare features in these strands of literature.

Second, it contributes to the literature documenting the importance of management practices (Bloom and Van Reenen, 2007; McKenzie and Woodruff, 2017), including experimental work that tests for informational constraints in their adoption (Bloom et al., 2013; Bruhn, Karlan and Schoar, 2018; Anderson and McKenzie, 2022; Iacovone, Maloney and McKenzie, 2022) and showing that information provision works better when complemented with behavioral interventions (Lafortune, Riutort and Tessada, 2018; Dalton et al., 2021). This study contributes with the insight that a purely behavioral treatment can improve business planning and lead to better performance, while additional information can potentially be harmful by crowding out engagement with the nudge. Moreover, it shows that a cheap and scalable intervention such as messaging managers can be an effective tool for helping small firms adopt better practices, especially when distributed during a valuable time window such as the weeks before a major sales event (McKenzie, 2021).

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

[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.

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 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.[5]

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 third-party apps to the online store.

2.2 Black Friday

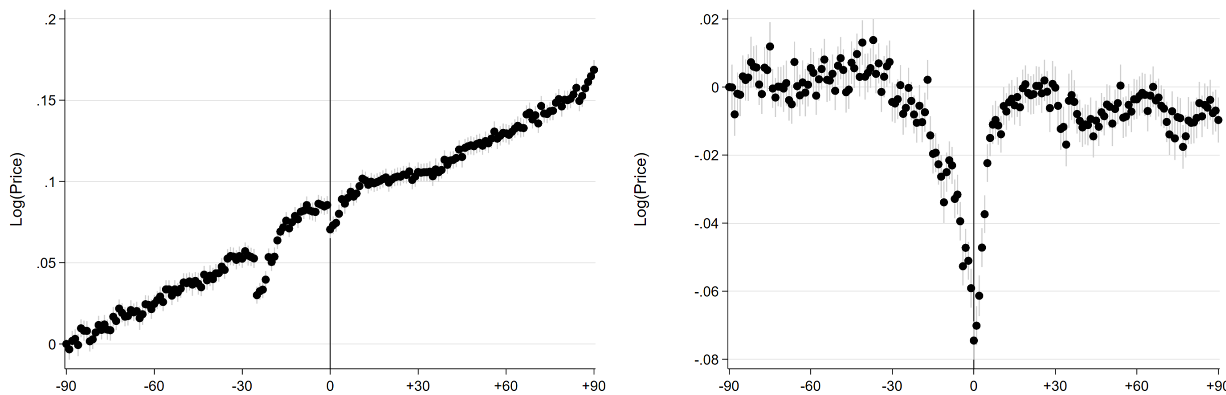
The experiment leverages Black Friday as an opportunity for online retailers to increase their sales and to expand their client base. The tradition of having large sales events on the Friday after Thanksgiving is said to have started in Philadelphia (PA), United States, in the 1960s, turning especially 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 started in Argentina and Brazil in 2013 and 2010, respectively. Moreover, in many countries, BF is followed by Cyber Monday, which is another sales event, focused on e-commerce, which leads many online retailers to offer discounts throughout the weekend.

Black Friday is a massive sales event. According to the largest web-host for online retailers around the world, during the 2022 event, 52 million consumers purchased from their clients, spending $ 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. This increase is driven in part by

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

[5]I do not observe who manages the online store. Based on anecdotal evidence from platform executives, it is usually the owner of the firm or a close relative (e.g., a tech savvy son or daughter), but it may also be an employee.

Figure 1: 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.

price reductions – famously offered through discounts and promotions. Figure 1 presents the evolution of transacted prices (controlling for product fixed effects) during 180 days around BF, revealing price reductions of roughly 1.5% in Argentina and 7% in Brazil. Finally, Black Friday is also a major opportunity to attract customers and 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 expect behavioral frictions, such as procrastination, to be less prevalent compared to day-to-day operations. In other words, if managers procrastinate around a high stakes situation like BF, they likely procrastinate at least as much during regular times. This would imply that this paper provides a lower bound for the prevalence of behavioral frictions around business planning.

3 Methods

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

3.1 Data

The platform provided data on online operations and firm characteristics. These data include daily sales at the product level between January 1, 2021 and March 15, 2022 (in quantities and in revenue); 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 marketing 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 three groups: T1 ("*nudge*"), which received a nudge to engage with BF; T2 ("*nudge + info*"), which received T1's nudge plus additional information on a potential pricing strategy; and C, a pure control.

The nudge (T1) consisted of of 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 nudge managers to plan their pricing and advertising strategies for BF. It includes a reminder that BF is approaching and a small incentive to take action and plan their pricing and advertising strategies. Importantly, participation in the raffle was negligible: 168 firms submitted their flyer (1.74% of treated managers), which is reassuring that it did not affect managerial incentives, but only helped increase the salience of the message. Moreover, the message uses language that highlights the costs of postponing action, both directly (e.g., "*a great opportunity to increase sales*;" "*don't miss the opportunity!*") and indirectly, by creating a sense of urgency ("*Black Friday is just around the corner!*;" "*Have you already planned yours?*"). For these reasons, the message can be interpreted as addressing procrastination around planning (Akerlof, 1991; O'Donoghue and Rabin, 1999).

The "nudge + info" arm (T2) consisted of 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? 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!*

The additional information refers to the loss-leader pricing strategy. It is a more sophisticated strategy than flat discount rates and thus, potentially useful information to managers. The literature on micro-entrepreneurship in developing countries has shown that pricing is a challenging decision and we know little about how the price-setting process works (Quinn and Woodruff, 2019). For example, McKenzie and Woodruff (2017), show that only 24% and 44% of small firms in Mexico and Chile had visited at least one competitor to check their prices in the last 3 months. Even in a low search cost context such as e-commerce, platform executives provided anecdotal evidence that managers mostly follow simple heuristics to price their products, such as variable costs plus a mark-up they consider reasonable.

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 sales (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 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).[6] All communications were distributed by the platform, who regularly sends messages through these same channels. Open rates by the start of BF were 33% for the first round (email) and 55% for the second round (in-platform). Overall, 72% of treated managers read at least one message and 16% read both of them.

3.3 Empirical Model

I estimate intent-to-treat (ITT) effects throughout the paper, relying on treatment randomization for identification. I estimate the effects of the nudge by comparing T1 (nudge) to C (control) and the effects of the information treatment by comparing T2 (nudge + info) to T1 (nudge). I obtain dynamic treatment effects when pre- and post-treatment data are available by estimating event-study models:

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

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

[6] During the second round of communications there was a mistake in the distribution of messages to Argentine firms. Those assigned to T1 received both messages, while those assigned to T2 received neither. However, since the information treatment had mild *negative* effects, this contamination would, if anything, reduce the effect of the nudge on Argentine firms, providing a lower bound for the true effect. Moreover, as Brazilian firms were not affected by this error, I can replicate the analysis only on them. In the Appendix, I show that all main results of the paper are robust to dropping the Argentine firms from the sample.

1 when firm i received treatment m periods before t. The vector β captures the dynamic treatment effects with respect to a baseline period, which I choose to be the one right before the onset of the experiment. Standard errors are clustered at the firm level throughout the paper under this empirical 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 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 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. Columns (2) and (4) also include strata fixed effects.

Table 1: Balance table

	Treatment 1		Treatment 2	
	(1)	(2)	(3)	(4)
Log(Sales Aug-Oct '21)	0.002	0.008	-0.004	-0.008
	(0.003)	(0.005)	(0.003)	(0.005)
Months since entry	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
0-1 employees	-0.015	-0.016	-0.044	-0.046
	(0.042)	(0.042)	(0.042)	(0.042)
2-5 employees	-0.015	-0.016	-0.045	-0.047
	(0.042)	(0.042)	(0.042)	(0.042)
6-25 employees	-0.033	-0.034	0.016	0.016
	(0.045)	(0.045)	(0.045)	(0.045)
Reports employees	0.012	0.011	0.034	0.038
	(0.042)	(0.043)	(0.042)	(0.043)
0 B&M	-0.002	-0.001	0.015	0.014
	(0.065)	(0.066)	(0.065)	(0.066)
Showroom only	-0.012	-0.011	0.021	0.019
	(0.066)	(0.067)	(0.066)	(0.066)
1 B&M	0.005	0.006	0.030	0.029
	(0.065)	(0.066)	(0.065)	(0.066)
2-5 B&M	0.014	0.015	-0.014	-0.016
	(0.067)	(0.068)	(0.067)	(0.068)
Reports B&M	-0.003	-0.007	-0.012	-0.007
	(0.066)	(0.067)	(0.065)	(0.067)
Instagram	0.011	0.011	-0.024	-0.025
	(0.019)	(0.020)	(0.019)	(0.020)
Facebook	-0.005	-0.005	-0.001	-0.000
	(0.010)	(0.010)	(0.010)	(0.010)
Google analytics	-0.002	0.015	-0.003	0.016
	(0.009)	(0.024)	(0.009)	(0.024)
Integrated apps	0.001	0.002	0.002	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Strata FE	No	Yes	No	Yes
Control mean	0.33	0.33	0.33	0.33
F-test p-value	0.99	0.92	0.35	0.23
Obs.	14494	14494	14494	14494

Note: Each column regresses treatment group indicators on a set of baseline characteristics. Columns (2) and (4) include strata FE.

4 Results: Nudge treatment

This section presents the results from the nudge treatment. First, 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 it didn't affect pricing, it led to more effective advertising and inventory management. Second, it demonstrates that planning resulted in higher revenue, driven by an increase in quantities sold and robust to alternative specifications.

4.1 Marketing strategy

The experiment aimed to engage managers with planning in advance of BF. Moreover, it targeted a specific business practice: the marketing strategy. 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 planning.

Marketing is a fundamental aspect of online retailers business, especially when they don't operate through a centralized marketplace. The usual approach among smaller firms is to focus their advertisement efforts on social media platforms, especially Facebook and Instagram, which are free. For example, 72% of firms in the sample have a Facebook account and 95% have an Instagram account.[7]

Figure 2 presents the effects of the nudge on the likelihood of advertising discounts.[8] We observe that firms assigned to receiving the nudge display a higher likelihood of around 0.0075 percentage points (pp) at its peak, 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.

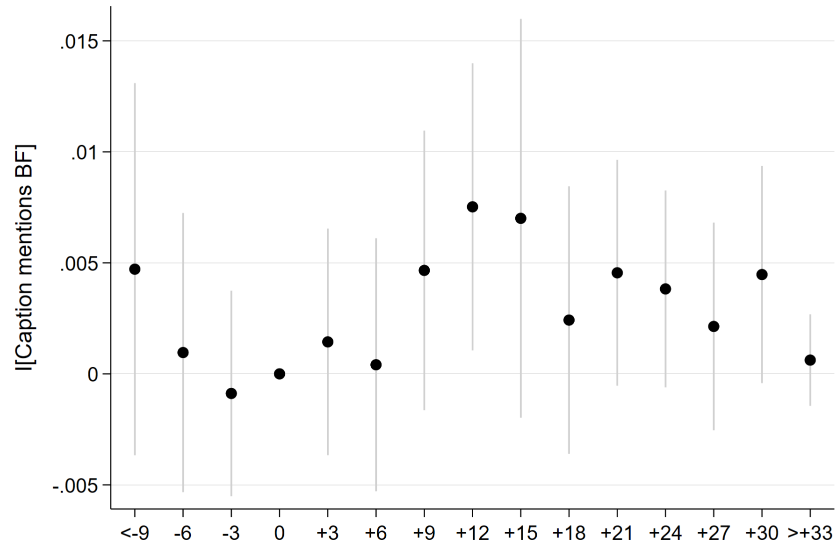
Reassuringly, we don't observe statistically significant differences between treatment and control before the experiment. We also observe a null effect in the medium run, as the last coefficient —which incorporates all observations between 30 and 120 days after the experiment— is virtually equal to zero.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

Finally, Figure A2 shows that the nudge did not increase advertising in general, as the likelihood of posting content on Instagram did not change. This implies that the intervention led managers to substitute generic advertising with advertising discounts, which may reflect a strategic decision to not saturate the attention of prospective clients with other content.

[7] Firms can also pay to advertise specific posts, but this is less common among small firms. Unfortunately, the data do not indicate whether firms invest money in ads campaigns.

[8] Specifically, it plots the coefficients from Equation 1 under 3-day time periods where the outcome variable is measured at the daily level and takes value 1 if any post that day mentions a term related to BF or discounts, and 0 otherwise.

Figure 2: 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 the nudge treatment. 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.

Moreover, firms in the sample are generally very active on Instagram: the probability of posting at least once on any given day is 29% and the average number of posts per day is 0.46 during the sample period.

4.2 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 another essential managerial practice that was not targeted by the nudge. Results show that, as of the day before BF, treated firms have more products listed and have more products with positive stock.

Inventory management plays a key role in a firm's operations, with multiple papers documenting its importance among firms in developing countries (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.

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%).

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

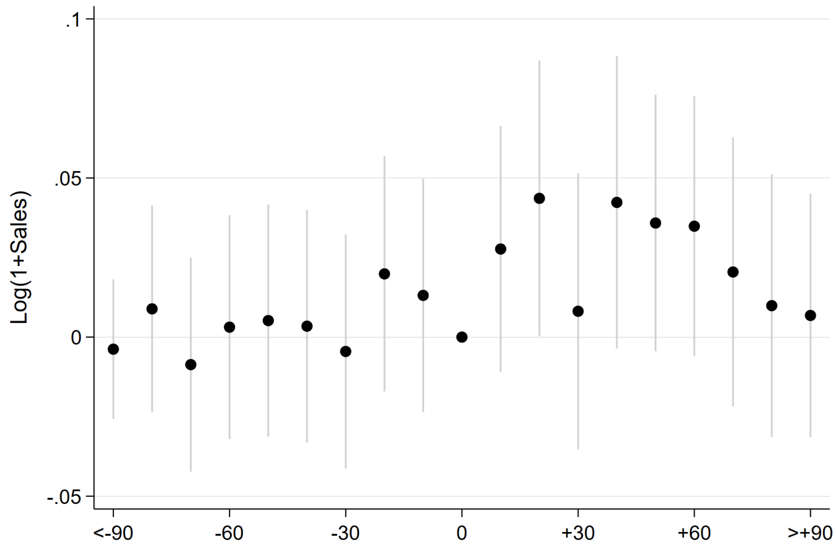
This unexpected finding —inventory management was not a targeted practice in the intervention— implies that the nudge induced a more holistic operational perspective. Indeed, this effect is consistent with the nudge successfully addressing procrastination: Managers know what they have to do, but they are behaviorally biased to postpone it.

4.3 Pricing strategy

Leveraging data on firms' full product listings on the day of BF, Table A3 presents the effects of the nudge on different measures of pricing, based on Equation 2.

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 before the intervention). 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. Indeed, 73% of firms in the sample offer at least one discount that day. This result is also reassuring that the nudge did not entail information provision, as there is no evidence that receiving the nudge increased participation in the event.

Figure 3: Log(1+sales), nudge treatment



Note: The outcome variable is the log-transformed value of daily sales plus 1. Plotted coefficients correspond to the nudge 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.

4.4 Revenue

So far we have seen that addressing behavioral frictions through a nudge can help managers plan in advance of a major sales opportunity, adopting a holistic approach to business strategy. In this section I look at the evolution of revenue to answer whether such frictions have a negative effect on firm performance.

Figure 3 plots the coefficients obtained from estimating equation 1 on log-transformed sales in US dollars as the outcome variable and assignment to the nudge as the treatment variable. It shows an increase of around 4% in revenue that lasts for 20 days after the onset of the intervention, fading away from there on and fully disappearing after 60 days. Reassuringly, there are no significant pre-trends, which would have violated the identification assumption. Importantly, there is also no evidence of a long-lasting effect, as the last coefficient in the event study stabilizes around zero.

Figure A3 also shows that effects are robust to an alternative specification, using *sales* in US dollars as the outcome variable and trimming the sample at the top 1% of the distribution to account for outliers.[9] The dynamics of the effect are similar in both cases, which oscillates

[9]This approach addresses concerns around the $log(1 + x)$ transformation, raised by recent research by Chen and Roth (2023).

around an increase of \$ 0.80 per day, which represents a 3.50% increase over a control group mean of \$ 23 per day at the baseline period.

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.[10] Interestingly, Figures A4 and A5 show that the increase in revenue is explained by an increase in quantities, with prices being broadly unaffected by the intervention, especially in the periods when revenue grows the most. This is consistent with profits growing at roughly the same rate as revenue during the post-treatment period.

Overall, we observe a significant positive effect of the nudge on firm performance, most pronounced in the period covering the few days before BF, BF, and the week after that. These dynamics are in line with the effects observed on planning: Treated managers significantly increase their advertising between 3 and 5 days before BF, which immediately converts into higher sales. The fact that revenue stays significantly higher for up to 60 days after the intervention may reflect short term gains in customer base, possibly triggered by the importance of Black Friday to attract customers. Alternatively, the lack of end-line effects implies that the intervention does not reduce firm exit.

4.5 Treatment effect heterogeneity

This section uncovers heterogeneities in the effect of the nudge across different types of firms, introducing important nuances in the effectiveness of nudges to improve firm performance. The analysis builds on a machine learning methodology that predicts conditional average treatment effects (CATE) for each firm, based on a causal forest estimation (Athey, Tibshirani and Wager, 2019).[11] Findings show that effects were stronger among larger firms in the clothing industry who are more engaged with social media and web analytics.

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

Table 3 presents the results, where firms are grouped based on being below or above

[10] Although section 4.3 shows that listed prices are not affected by the nudge, sales could be driven only by products offered at heavy discounts.

[11] 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 median CATE. In particular, I test whether certain firms characteristics are associated with a stronger treatment effect. Column 3 shows the differences in the mean value of each characteristic between firms with above-median and below-median CATE, and column 4 provides the p-value adjusting for multiple hypothesis testing based on List, Shaikh and Xu (2019).

We observe that the nudge had a stronger effect on more established firms, including those with higher pre-treatment sales, older, with more employees, and with offline presence (brick-and-mortar stores). Although in principle one could expect smaller firms to see their performance affected by behavioral frictions, these results indicate that these are also binding beyond micro-enterprises or self-employed individuals running simple businesses. Well established firms, with over two years of age on average and highly likely to have at least one brick-and-mortar store, tend to enjoy higher returns from an intervention addressing behavioral frictions in their business planning. Additionally, these results are also consistent with more established firms having the capacity to act on the nudge and having more at stake during a major sales event such as Black Friday. In particular, there may be scale economies, where advertising and inventory management are strategic complements with firm size.

The analysis also shows that the nudge was significantly more effective on firms in the clothing industry and more actively engaged with social media and web analytics, as captured by the positive association with having a Facebook account and Google analytics. The clothing industry is a highly competitive sector in online retail; small firms within this sector tend to be very active on social media. Facebook usage reflects a more active engagement with social media (recall that virtually all firms already use Instagram), and Google Analytics implies a more sophisticated use of online tools to run their business. As with the positive association with firm size, these results may also reflect the importance of pre-established capabilities to unlock the benefits of the nudge. Managers who are already predisposed to run social media campaigns and are relatively sophisticated in the use of online tools are the ones who react to the nudge in an effective manner.

Finally, the nudge was more effective on Argentine firms. As this result arises after accounting for a large set of firm characteristics, we may consider market characteristics to understand such heterogeneity. The more salient difference between the two countries in this context is the timing of another big sales event: Cyber Monday. While in Brazil it takes place on the Monday following Black Friday (as in the US), in Argentina it takes place a few weeks before. This implies that Argentine consumers may be relatively less responsive to BF discounts, making it especially important to plan the advertising strategy, in order to attract attention and increase sales.

Table 3: Heterogeneous treatment effects on sales

Variable	(1) Low Predicted TE	(2) High Predicted TE	(3) Diff.	(4) MHT p-value
Pre-treatment sales (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
Facebook Pixel	0.737	0.736	-0.001	0.986
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 sales during the 20 days after the intervention, following Athey, Tibshirani and Wager (2019). Column 3 provides the difference in means and column 4 the p-values adjusting for multiple hypothesis testing, following List, Shaikh and Xu (2019). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5 Results: Information treatment

This section presents the results of the information-provision intervention. First, it shows that providing managers with information on a possible discount strategy —the loss-leader approach— had little effect on managerial planning, even around pricing. Second, it shows that adding the information treatment canceled out the benefits from the nudge in terms of firm performance.

The information treatment was designed to address a potential informational constraint around a challenging decision faced by small firm managers: how to price their products. This turns especially relevant around a major sales event such as Black Friday, where discounts play a key role in attracting customers and driving sales. For this reason, to the extent that managers are not aware of the loss-leader approach, we would expect some firms to find it a marginally better strategy and, thus, adopt it.

However, Table A4 shows that the information treatment did not affect pricing decisions. In particular, it didn't impact the share of discounted products within each firm, which is expected to be lower under the loss-leader strategy. This may reflect weaker-than-anticipated informational constraints: If managers had not been aware of this strategy, receiving the message should increase the likelihood of implementing it in the margin. Figure A1 also shows insignificant effects on advertising.

Alternatively, Table A2 presents negative effects of the information treatment on inventory management. Although these are noisily estimated, the difference between the control group and the "nudge + information" treatment group becomes economically small and statistically insignificant. This implies that the information treatment may have canceled out the positive effect of the nudge on this (non-targeted) aspect of planning. Under the nudge alone, managers react by planning more effectively their overall strategy for BF. However, under the longer message including information that did not turn out to be useful (as reflected in the lack of adoption of the loss-leader approach), managers fail to plan at least some aspects of their operations.

Crucially, Figures A6 and A8 show that the information treatment negatively affected performance, undermining the benefits of the nudge. This can also be seen in Figures A7 and A9, showing that firms in the "nudge + info" treatment group performed similar to those in the control group.

Why was the additional information detrimental to performance? Besides having lower inventories, managers that received this treatment were also less prone to engaging with the nudge: The likelihood to submit the flyer for the raffle is significantly smaller within this group. Specifically, 1.45% of managers in the nudge + info group submitted their flyer, compared to 2.03% in the nudge only group (-29%, p=0.03).[12] This pattern could reflect

[12]This is also robust to using only the Brazilian sample: 1.32% v. 2.38%, respectively (-45%, p<0.01). Note also that the higher difference among Brazilian firms is in line with the expected lower bound effects

information overload or a crowding out effect on managers' attention budget, which is now partly devoted to the additional information at the expense of the nudge.

6 Conclusion

Managerial practices are a crucial input of the firm's production function. A growing literature has found that different types of interventions targeting managerial practices can be beneficial for small firms, especially in developing countries. These interventions mostly focus on business training programs, which tend to be especially powerful when combined with behavioral interventions. 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 in advance of a major business opportunity. The main result is that nudging managers to plan resulted in approximately 4% higher revenue over a period 20 to 60 days. Evidence on mechanisms indicates that treated managers display behavior that is consistent with more effective advertising and inventory management, albeit no changes in pricing. Moreover, it was the larger firms who benefited the most from the nudge, suggesting that pre-established capabilities play an important role in unlocking the benefits of the intervention. Evidence from a second treatment arm that combined the same nudge with additional information shows that information provision treatments can lead to information overload, crowding out the behavioral treatment and thus undermining its benefits.

Taken together, this study provides evidence that behavioral frictions —mostly related to procrastination— among managers can hinder firm performance, even in a context of relatively sophisticated firms. It also shows that scalable interventions that leverage mobile and internet technologies can lead to significant improvements for micro-enterprises, by helping to address these behavioral frictions. Nevertheless, the design of such interventions should take into consideration the attention budget of individuals, as providing too much content can reduce engagement with other parts of the treatment.

obtained under the full sample.

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Appendix

Context

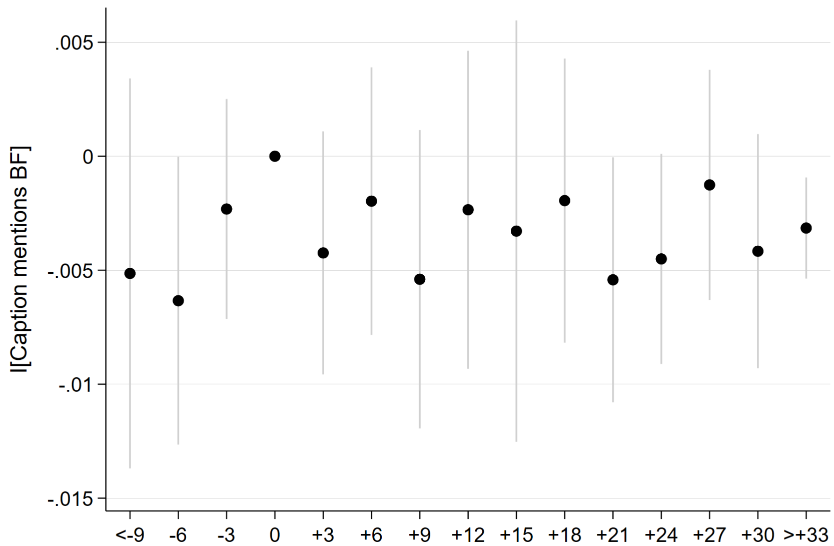
Table A1: Sample characteristics

	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 sales 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.

Additional results on marketing strategy

Figure A1: Advertising discounts on Instagram, information treatment



Note: The outcome variable is an indicator taking value 1 if the firm made a post on Instagram mentioning discounts at least once in the day. Plotted coefficients correspond to the information treatment. 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.

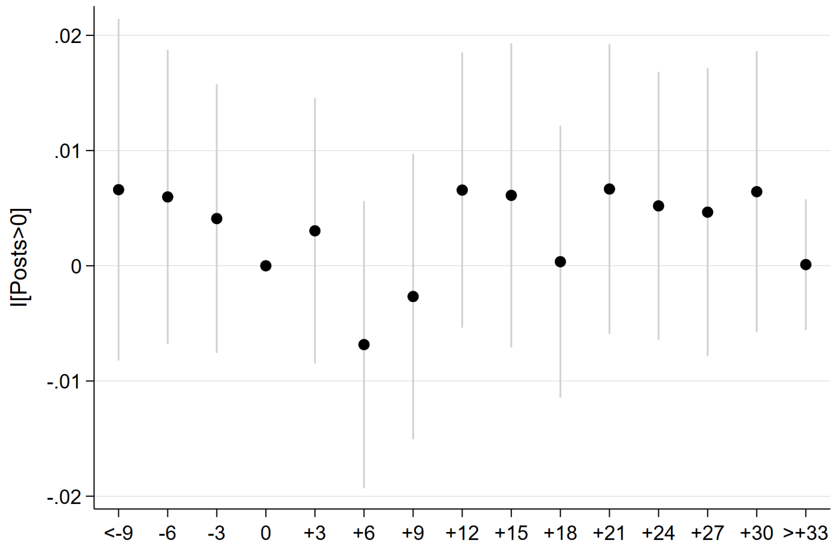
Additional results on inventory management

Table A2: Inventory management, information treatment

	log(products)	log(products) | stock>0	log(products) | stock>100
	(1)	(2)	(3)
Information	-0.02	-0.02	-0.08
	(0.03)	(0.03)	(0.06)
Strata FE	Yes	Yes	Yes
Control mean	5.66	5.66	5.88
Obs.	9661	9643	5926

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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure A2: Posting activity on Instagram, nudge treatment



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 the nudge treatment. 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 A3: Pricing, nudge treatment

	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: Pricing behavior based on 5 most sold products. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

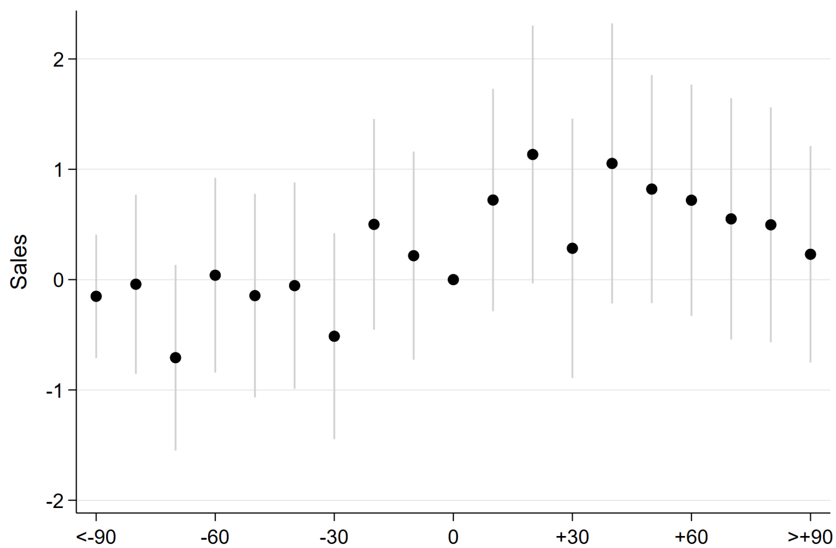
Table A4: Pricing, information treatment

	Full listing			Top 5 products		
	(1)	(2)	(3)	(4)	(5)	(6)
	Any disc.	Log(Avg. Price)	Share disc. Prod.	Any disc.	Log(Avg. Price)	Share disc. Prod.
Information	0.003	0.012	-0.004	-0.003	-0.009	-0.005
	(0.009)	(0.020)	(0.005)	(0.009)	(0.026)	(0.009)
Strata FE	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.739	6.266	0.204	0.310	5.918	0.271
Obs.	9664	9642	9664	9664	8307	8307

Note: Pricing behavior based on 5 most sold products. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

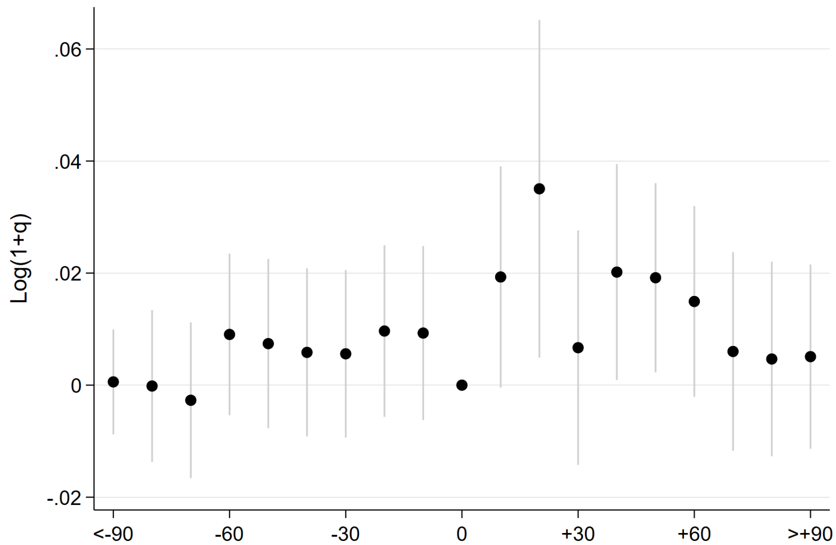
Additional results on revenue

Figure A3: Sales (trimmed top 1%), nudge treatment



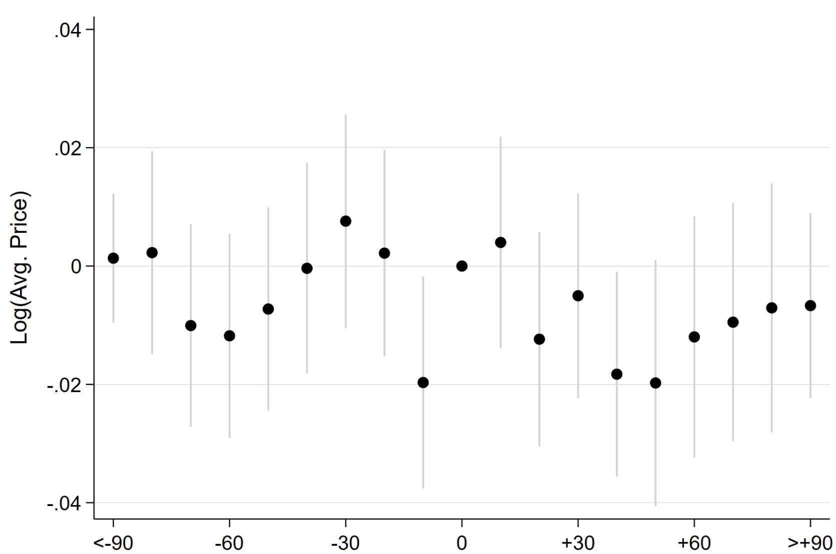
Note: The outcome variable is sales, trimmed at the top 1%. Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard errors clustered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

Figure A4: Quantities sold, nudge treatment



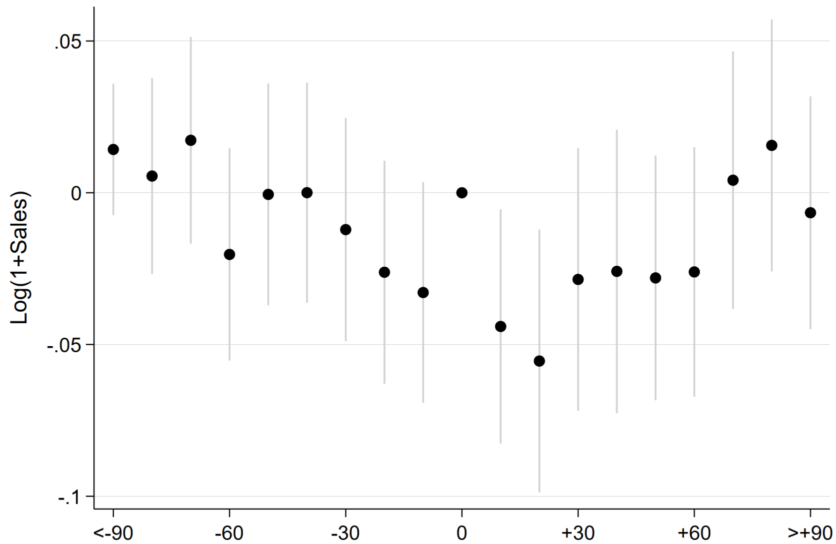
Note: The outcome variable is the log of 1 plus product quantities sold per day. Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard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

Figure A5: Average price, nudge treatment



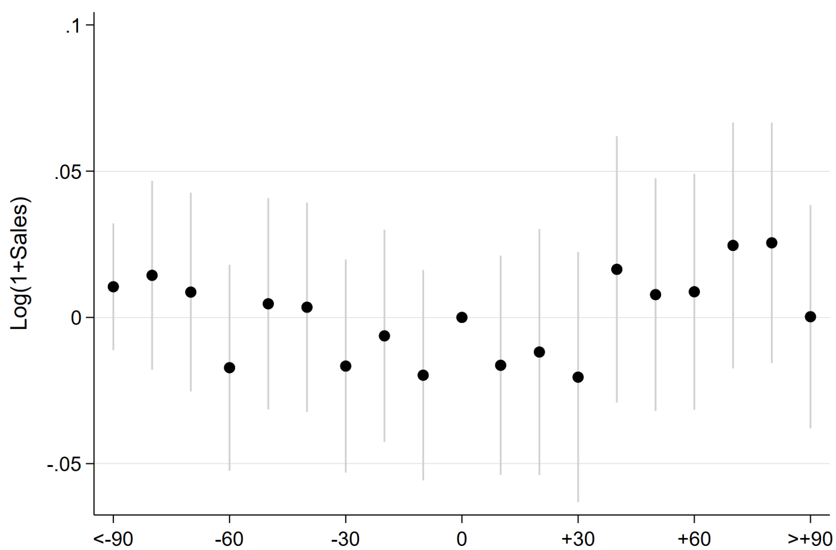
Note: The outcome variable is the log of 1 plus revenue over quantities sold (average daily price). Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence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

Figure A6: Log(1+sales), information treatment



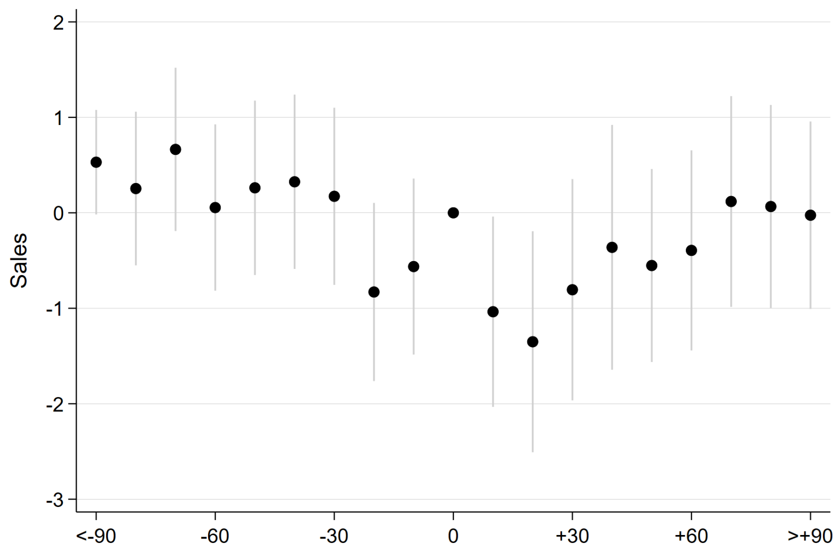
Note: The outcome variable is the log-transformed value of daily sales plus 1. Plotted coefficients correspond to the information treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard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

Figure A7: Log(1+sales), nudge + information treatments



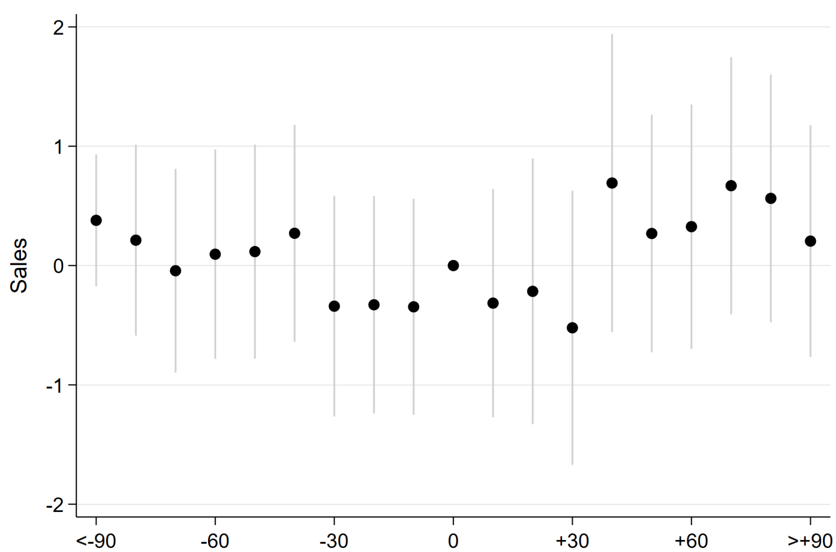
Note: The outcome variable is the log-transformed value of daily sales plus 1. Plotted coefficients correspond to the information treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard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

Figure A8: Sales (trimmed top 1%), information treatment



Note: The outcome variable is sales, 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.

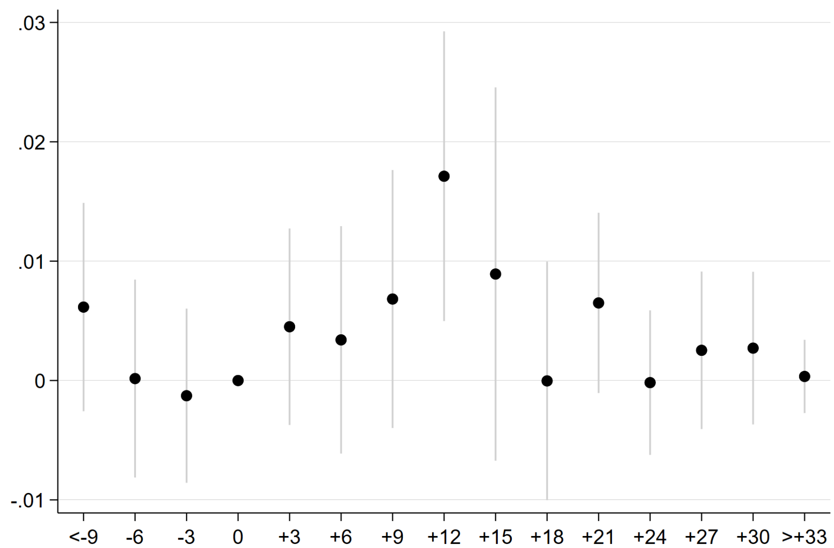
Figure A9: Sales (trimmed top 1%), nudge + information treatments



Note: The outcome variable is sales, 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.

Replication under Brazilian sample only

Figure A10: Brazil only: Advertising discounts on Instagram



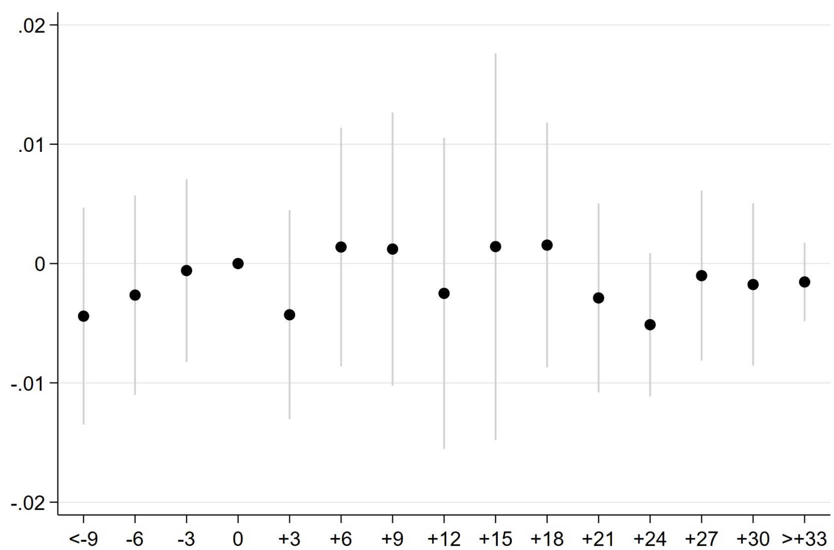
Note: Brazilian firms only. The outcome variable is an indicator taking value 1 if the firm posts on Instagram and mentions discounts at least once in the day. Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 3-day bins. Period 0 corresponds to the three days before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

Table A5: 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

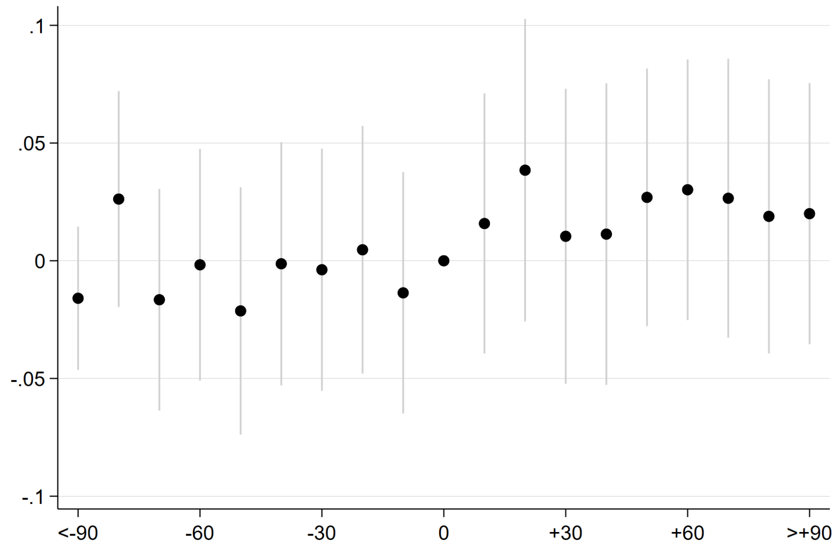
Note: Brazilian firms only. Column 1 regresses the log of number of products listed as of the day before Black Friday (BF). Columns 2 and 3 regress the the analogous considering only products with positive stock and with more than 100 units in stock, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p 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

Figure A11: Brazil only: Advertising discounts on Instagram, information treatment



Note: Brazilian firms only. The outcome variable is an indicator taking value 1 if the firm made a post on Instagram mentioning discounts at least once in the day. Plotted coefficients correspond to the information treatment. 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.

Figure A12: Brazil only: Log(1+sales), nudge treatment



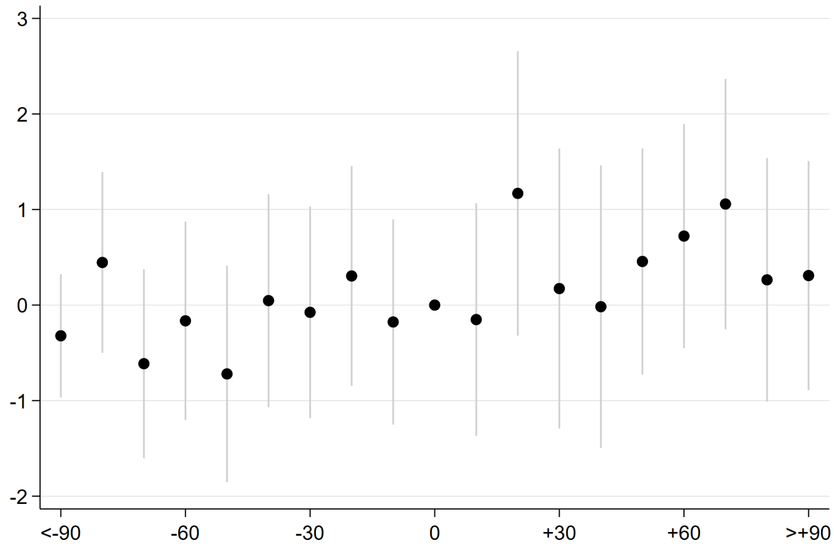
Note: Brazilian firms only. The outcome variable is the log-transformed value of daily sales plus 1. Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence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

Table A6: Brazil only: Inventory management, information treatment

	log(products)	log(products) | stock>0	log(products) | stock>100
	(1)	(2)	(3)
Information	-0.02	-0.03	-0.11
	(0.04)	(0.05)	(0.10)
Strata FE	Yes	Yes	Yes
Control mean	5.68	5.69	5.97
Obs.	4543	4530	2694

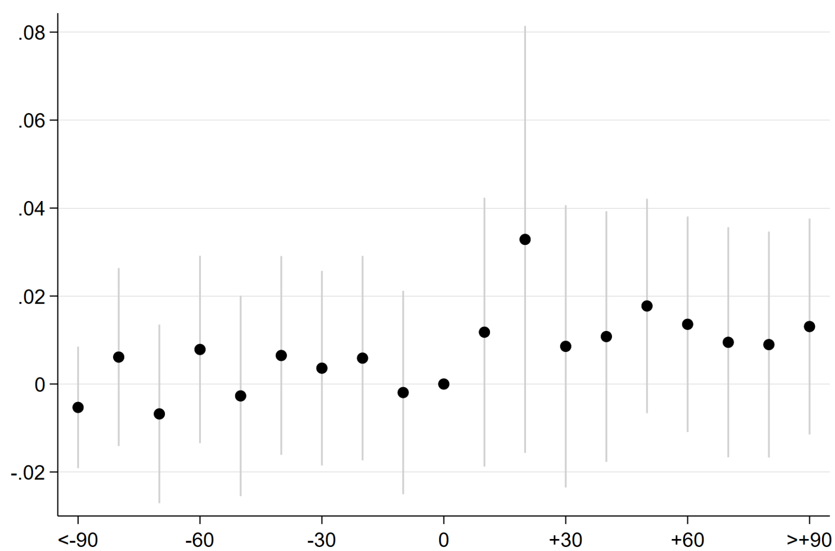
Note: Brazilian firms only. Column 1 regresses the log of number of products listed as of the day before Black Friday (BF). Columns 2 and 3 regress the the analogous considering only products with positive stock and with more than 100 units in stock, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p 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

Figure A13: Brazil only: Sales (trimmed top 1%), nudge treatment



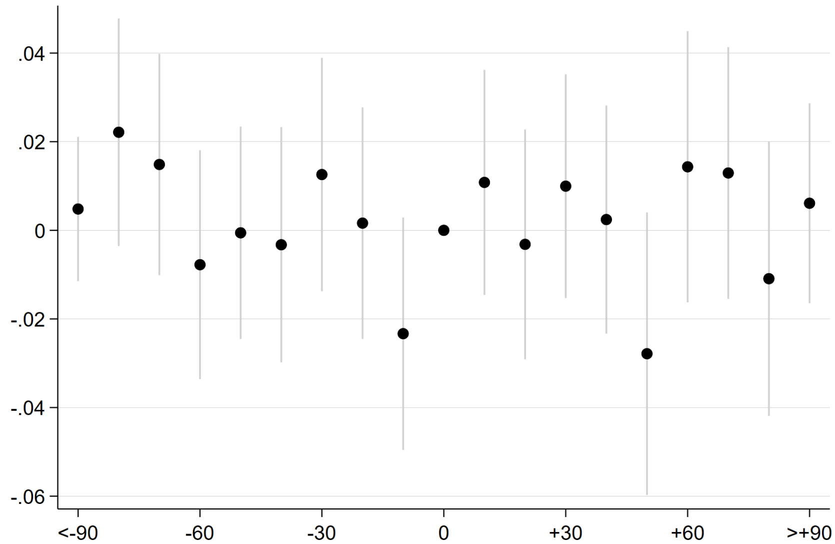
Note: Brazilian firms only. The outcome variable is sales, trimmed at the top 1%. Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence intervals. Standard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

Figure A14: Brazil only: Quantities sold, nudge treatment



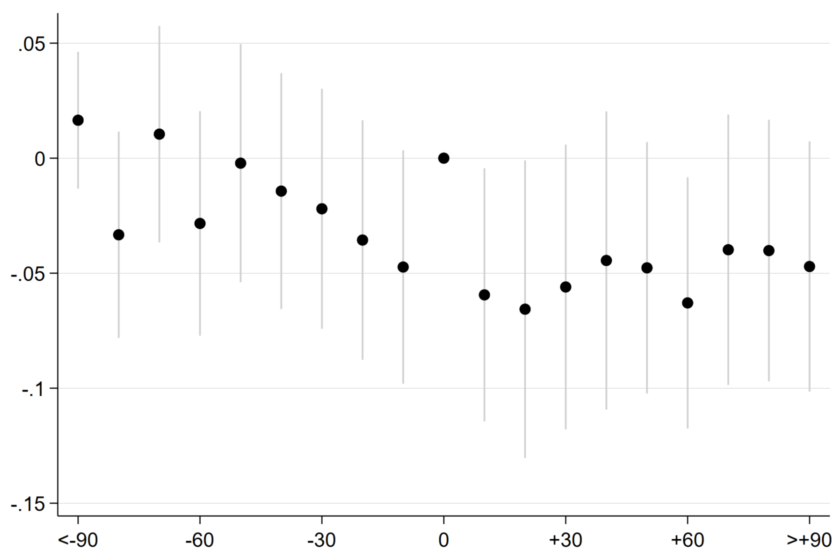
Note: Brazilian firms only. The outcome variable is the log of 1 plus product quantities sold per day. Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of messages. 95% confidence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

Figure A15: Brazil only: Average price, nudge treatment



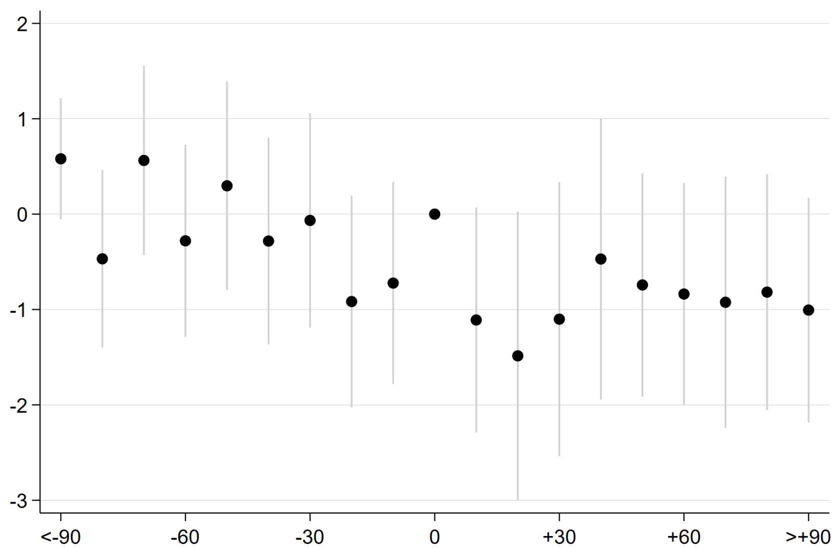
Note: Brazilian firms only. The outcome variable is the log of 1 plus revenue over quantities sold (average daily price). Plotted coefficients correspond to the nudge treatment. Time-period corresponds to 10-day bins. Period 0 corresponds to the ten days before the distribution of the first round of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

Figure A16: Brazil only: Log(1+sales), information treatment



Note: Brazilian firms only. The outcome variable is the log-transformed value of daily sales 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 A17: Brazil only: Sales (trimmed top 1%), information treatment



Note: Brazilian firms only. The outcome variable is sales, 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.