Sophisticated Consumers with Inertia: Long-Term Implications from a Large-Scale Field Experiment

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Abstract

Consumer inertia, the tendency to remain inactive, is a robust and well-documented phenomenon. However, if consumers are aware of their future inertia they can act to mitigate its effects on their outcomes. Using a large-scale randomized field experiment with a leading European newspaper we investigate consumer response to inertia inducing subscription contracts and study, in the same setting, both the actual inertia, and the inertia consumers anticipate before it actually takes place. We vary the promotional subscription price, the duration, and whether the contract automatically renews by default, or not, after the promotional period. Indeed, we find strong inertia (53%-75% chance of not taking a desired action within a month), such that the auto-renewal contract takers have a seven times higher tendency of continuing their subscription after the promotional period, relative to the auto-cancel contract takers. However, consumers preempt inertia; 24%-36% of potential subscribers avoid taking the auto-renewal offers, and 9% avoid subscribing at all for two years due to being offered the auto-renewal contract. Still, our estimates show that consumers underestimate inertia and, on average, anticipate one-sixth of it. Overall, even though auto-renewal generates a higher revenue in the short term, auto-renewal and auto-cancel are revenue equivalent after one year, but with fewer subscribers in auto-renewal. Our results highlight the often-ignored effects of potentially exploitative inertia-inducing contracts: lower take up in the short- and long-run driven by sophisticated consumers.

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1 Introduction

One of the most researched and widely documented characteristics of consumer behavior is inertia—the tendency of an individual to take no action and stay in the same state as before. For example, an individual is likely to pay a higher price for a subscription if they previously enrolled in it, but will not subscribe under this price if they were not already enrolled.

Inertia has consequences for firms and policy makers trying to assess the functioning of markets. If consumers are unresponsive to worsening of an option they previously chose, it might give incumbents undue advantage. This behavior incentivizes firms to offer choices that are better in the short run but worse in the long run. Further, they will design their products such as to increase inertia.

Crucially, these consequences of inertia depend not just on the degree of inertia, but also on whether consumers are aware of their inertial tendency and how they account for it in their decision making. In a world where consumers are not aware of their inertia, or are myopic about their future inertial behavior, they will not preempt it and get stuck with choices that appear good initially but are worse in the long run. On the other hand, if consumers are aware of their behavioral limitations, they will account for them in their decision making and avoid getting into situations where they might get exploited due to inertia or find other ways to limit its effects. This consideration will discourage firms from creating situations that might be construed as exploitative by consumers. Hence, even if consumers have inertia, its negative impact is mitigated due to their self-awareness. Of course, it is plausible that consumers are heterogeneous in their future inertia awareness, which can also be taken into account by firms by creating price, or inertia, discrimination (Eliaz and Spiegler, 2006).

In this paper we empirically assess how inertia affects consumer decisions in the context of digital newspaper subscriptions contracts. We ask the following specific questions. What is the degree of inertia in consumer subscription choices? What is the degree of awareness to future inertia and how does it affect subscription choices? How do these differ between consumers? And what are the effects of these forces on firm incentives and outcomes?

A prerequisite to empirically inferring whether consumers take into account their inertia while making decisions is observing their behavior before they make a choice that might put them in an adverse state due to inertia. In contrast, most of the previous literature documents inertia among individuals who have already made a choice and gotten into an inert state, and misses consumers who avoided entering an inertia-inducing situation (e.g., Handel (2013); Drake et al. (2022)). Additionally, to assess consumer sensitivity to inertia, we need variation in the degree of future inertia caused by the choices consumers face, which is rarely observed. Further, we need the variation in inertia to be exogenous, which is challenging to obtain.

We overcome these challenges by running a large-scale field experiment in which we randomize the terms of the subscription offers received by 2.1 million readers who hit the digital paywall of a large European daily newspaper. Our experiment is a 3-way full factorial ($2 \times 2 \times 2$) design; a reader in our experiment is offered a subscription promo that (1) either automatically renews, by default, into a paid subscription for those who take the promotion unless they explicitly cancel it, or does not automatically renew but requires the promo taker to click to enroll into a paid subscription (which we call an auto-cancel offer), (2) has a promotional trial period for either 4 weeks, or 2 weeks, (3) has a promotional price of either €0, or €0.99. Importantly, all other aspects of the contract, including the information consumers need to provide to take up the offers are the same across the eight experimental groups. We then follow these potential subscribers

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1Such suggestive evidence is by Shui and Ausubel (2004) showing that consumers are more likely to take low introductory-rate credit card offers.

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for 2 years and observe their interaction with the platform and use the treatment arms to learn about inertia and responses to it.

Comparing the subscription take-up behavior during the promo period between those who receive the auto-renewal promo and those who receive the auto-cancel promo tells us whether consumers are sensitive to the future possibility of being defaulted into the paid subscription. We expect no differences between the two groups if consumers overlook the future outcomes, or believe (e.g., due to overconfidence) that they would cancel the subscription before it renews if they do not want the paid subscription. The difference in continuation of subscription after the promo time period helps us assess the actual degree of inertia caused by taking up the auto-renewal contract.

The experimental variation in price and promo duration serves the following purposes. First, it enables us to estimate “learning” or the effect of product trial on the long-term subscription rate, which is useful in interpreting the effect of serving the auto-renewal vs. auto-cancel offer. Second, simultaneously varying the promotional price and the subscription renewal terms helps us quantify in monetary terms how much individuals value not getting defaulted into the subscription after the promotion ends. Third, simultaneously varying the promotional price and duration allows us to quantify the average value of subscription, which in turn enables us to calibrate the consumers’ expected inertia at the time they take up the subscription.

Our first main finding is that consumers are less likely to take a future-inertia-exploiting contract. We find that 24% fewer readers take up any newspaper subscription during the promotional time period when offered an auto-renewal offer, relative to an auto-cancel offer. Thus indicating that the some readers recognize and adapt their behavior to future auto-renewal terms and, overall, they prefer the promo that does not convert into a paid subscription by default. Comparing this effect with the sensitivity to the experimentally varied promo price, we find that the average value of the auto-cancel offer is €2.64. Comparing the price effect with the effect of increasing trial duration helps us estimate the average value of the subscription.

Using these estimates, we quantify the consumer anticipated inertia—the incremental monthly likelihood of a user staying subscribed due to enrollment in an auto-renewal subscription as perceived by the user at the time of the subscription decision—to be 0.126, on average.

Second, we find the consumers are more inert than they anticipate. While the initial take-up is lower for the auto-renewal group, we find that the subscription-rate (the proportion of days a reader subscribes to the newspaper) is higher by 20% among those who received the auto-renewal offer, relative to the auto-cancel one for about four months post promotion. After this time, the difference in subscription rates declines. A year after the end of the promo, the subscription rate is higher in the auto-cancel relative to the auto-renewal group. Among those who take up an auto-renewal promo, we quantify the actual inertia to be 0.75, which is six times larger than our estimate of consumer’s perceived inertia at the time of promo take up. Examining the actual individual-level usage of the newspaper’s website, we see that auto-renewal subscribers rarely read the newspaper.

These data patterns together indicate the presence of significant consumer inertia that is not driven by predicted switching costs or by learning that they like the product. Individuals who subscribe to the auto-renewal offer continue to remain subscribed to the newspaper because of their initial auto-renewal promo take-up; they would not become high paying subscribers otherwise.

Third, offering inertia-inducing contracts discourages readers from engaging with the newspaper. On the extensive margin, the readers who were assigned an auto-renewal offer are 9% less likely to become paid subscribers at any time in the two years after the promotion, relative to auto-cancel. We do not observe such a push-back for other experimental factors; even though €0.99 vs. free promo and 2 weeks vs. 4 weeks both
cause 9% fewer people to subscribe during the promo period, their impact in the time period of two years after the promo are precise 0%. This pattern indicates that the negative impact on the extensive margin is the direct effect of the auto-renewal contract term, and not due to lower trial caused by it in the promo period. It also suggests that the medium term (up to four months post promo) increase in subscription-rates experienced by the newspaper is coming from few individuals who end up paying more on the intensive margin.

We can reconcile the above patterns by thinking of different consumer types. Our results suggest that most consumers are not naive or myopic about the future implications of the subscription contract terms. While some do take-up the auto-renewal contract and exhibit inertia, more than a third recognize and avoid a contract that might “exploit” them in the future, and another third are not inert and do not become high-paying subscribers. Only one-tenth of auto-renewal subscribers remain subscribed for more than three months and wouldn’t have under an auto-cancel contract. Further, a significant fraction of newspaper readers persistently avoid buying any subscription post-promotion because of being offered the auto-renew contract. Overall, while the newspaper gains revenue increase due to offering an auto-renewal contract in the medium-term after the promo period, those gains wash away after a while. Furthermore, the paper has negative incentive to do so in the long term because auto-renewal causes fewer people to subscribe, and their long-term subscription rate (days subscribed) is also lower.

Our findings cannot be explained by classic switching costs alone, regardless of whether consumers have perfect foresight about these costs [Klemperer, 1995], are completely myopic [Dubé et al., 2010], or due to stochastic switching costs. Perfect foresight implies that auto-renewal subscribers should remain subscribed post promo at similar rates to auto-cancel subscribers. In contrast, myopia about switching costs implies no effect on initial take-up. Finally, we also find long-term subscribers in the auto-renewal group to be of higher type (those that value the newspaper more) relative to the auto-cancel group, which goes against the prediction of a stochastic costs model; if hassle costs are stochastic, marginal rational consumers are more likely to remain subscribed, in the long term, in auto-renewal relative to auto-cancel leading to lower average "type" of auto-renewal subscribers.

We add a new perspective to a large literature [Brot-Goldberg et al., 2021; Choi et al., 2002; Della Vigna and Malmendier, 2006; Grubb and Osborne, 2015; Handel, 2013; Hortaçsu et al., 2017; Madrian and Shea, 2001] that documented high degree of inertia among takers who appear to be naive about their tendency to procrastinate. We differ by considering consumers who are able to avoid the inertia inducing engagement altogether (here, contract). While we also find subscription takers to exhibit substantial inertia in our context, our study highlights the importance of considering the entire population of consumers who considered the contract in assessing the overall impact of inertia in the marketplace. For instance, if we follow the literature and compare the likelihood of a user converting to a paid subscriber conditional on taking up the promo, we find the conversion rate to be 2000% higher for auto-renew takers relative to auto-cancel takers. However, accounting for all consumers, we see that there are actually fewer subscribers in auto-renew for any time horizon, and even the differences on the intensive margin are two orders of magnitude weaker.

We contribute to a much smaller literature that examines people’s response to future inertia, and how it affects companies’ decision making. For example, Reme et al. (2021) find that notifying existing subscribers of a mobile company about future plan changes leads to increased churn, even before prices change and even if their prices decrease. Meaning, some existing consumers are already inert and dormant, and the notification of future change draws their attention and potentially makes them aware that they might be inattentive again in the future. Rodemeier (n.d.) finds that consumers are aware of their lower likelihood of
redeeming a rebate, focusing on short-term interaction between a retailer and its consumer base. Like these papers, we find that future inertia is a factor that consumers take into account, but we focus on assessing the overall role of inertia by analyzing the longer-term behavior and considering the whole population (not just the takers) of consumers exposed to the contract. Further, our experiment is unique in eliciting consumer response to contracts that induce varying degrees of inertia. Indeed, the above papers find that for existing consumers exploitation of inertia is beneficial even if some of them are aware of it, while we find significant adverse consumer reactions to inertia inducing contracts. Finally, our paper also speaks to the conceptual way of incorporating inertia in models and empirical work. In the industrial organization tradition, inertia is operationalized as a transitory utility term to which consumers are fully naive (e.g., a brand coefficient as in Dubé et al. (2010)). In contrast, we find that a substantial share of potential subscribers avoid the service due to future inertia. Meaning that some are sophisticated about their future inertia. In the behavioral economics literature, inertia is an outcome of preferences that include either present-bias (DellaVigna and Malmendier 2004), over-confidence (Grubb and Osborne 2015), inattention (Brot-Goldberg et al. 2021), or habit formation (Allcott et al. 2021). Sophistication or partial sophistication regarding these forces may lead consumers to respond to future inertia. We do not distinguish between every possible source of inertia, but as mentioned above, we find support for partial sophistication, and can categorize consumers into different types (in the tradition of O’Donoghue and Rabin 1999, 2001).

Our paper also closely relates to the literature focused on firm marketing policies in contractual settings. Ascarza et al. (2016) show using a field experiment that a telecommunications company’s proactive churn prevention initiatives backfire, possibly because such interventions reduce inertia, for example, by reminding users of their low usage levels. Other papers focus on firm’s personalization and targeting policies. For example, Yoganarasimhan et al. (2021) assess the effect of free-trial duration on customer acquisition using a field experiment and show that policies that maximize short-run also perform well in the long run. Datta et al. (2015) show that customers acquired by promo subscriptions have a lower lifetime value to the firm. Focusing on newspaper user subscription discounts Yang et al. (2020) show the predictability of long-term outcomes based on short-term outcomes. Our paper differs in that we explicitly vary inertia-related contractual terms and assess the degree of consumer sophistication.

Our findings are relevant for businesses and regulators. While many companies try to make it harder for consumers to leave their services thinking that it increases their profits (“sludges” in Thaler and Sunstein 2021 language), we provide evidence that such practices, even if mild, can backfire due to two reasons. First, exploiting future inertia reduces initial take-up; Second, exploiting future inertia pushes new consumers to disengage from the company completely. Our finding of an economically significant negative reaction to auto-renewal contracts is relevant for regulatory agencies such as the FTC who worry about deceptive practices in subscription selling. Our evidence stands against the common wisdom and findings in the past literature which has assumed that people “passively” accept defaults (Benartzi et al. 2017). People in our study are susceptible to defaults, but most are also aware of these effects and successfully avoid them.

In the policy literature such practices are referred to as negative options, and the regulatory concerns about consumers getting deceived and being economically harmed by selling of negative options are widely discussed (see, for example, FTC May 2021, and Washington Post, June 2021 https://www.consumer.ftc.gov/articles/getting-and-out-free-trials-auto-renewals-and-negative-option-subscriptions and https://www.washingtonpost.com/business/2021/06/02/automatic-renewals-ftc-subscriptions/).
2 Empirical Setting

Our study was conducted in cooperation with a large European publisher that wishes to stay anonymous. The publisher is one of the largest daily newspapers in its market with strong readership in several European countries. The publisher represents a highly reputed quality news outlet similar to the New York Times or the Washington Post in the United States or the Guardian in the United Kingdom. It publishes daily news in the main categories of politics, economics and business, sports, local news, culture, society, science, digital, working life, and travel. In addition to the print newspaper, which started in 1945, the publisher has a digital platform which provides daily online news on its news website and mobile platforms. In 2018, approximately 12 million unique users visited our publisher’s digital platform.

The content on the digital platform is classified into three parts. One part is “always free” to any user. This content includes the main homepage, as well as the separate section homepages, agency news, breaking news, and also other commodity news which are also available for free elsewhere. Another part of the content is “always paid”, that is, it is available only to the platform’s paid subscribers. This part includes high quality exclusive content from the printed newspaper and commentaries. The rest of the content is “metered” and subject to a metered paywall. Readers are allowed to consume 10 news articles per week for free and then hit the paywall where they are prompted to purchase a subscription in order to be able to continue reading the metered articles. The metered articles are specifically produced for the digital news channels and are generated by a dedicated digital editorial team. Traffic referred from online search platforms (e.g., Google or Bing) and social media platforms (e.g., Facebook or Twitter) receives no special treatment, that is, a user referred by these platforms are subject to the same rules as any other.

Overall, such a content arrangement is sometimes referred to a soft-paywall which stands in contrast to a so-called hard-paywall whereby a reader needs to pay for reading any content (e.g., academic journals, Financial Times).

In addition to subscription revenue, the publisher earns revenue from displaying ads to its readers. Paid subscribers generally see fewer ads (e.g., no performance ads) and are allowed to use their ad blocker, if they wish to do so. Non-paying users see all ads and are not allowed to access the content using an ad blocker.

Tracking on the digital platform takes place via logins of registered users and cookies, and is in line with the European General Data Protection Regulation (GDPR). A user is assigned a cookie id once she hits the platform for the first time and is tracked on repeated visits as long as the cookie persists. Cookie-based tracking is not foolproof: A user can decide at any time to delete some or all cookies (i.e., active cookie deletion by clearing the cookies in her browser), and the same user may have multiple cookies if they access the website from multiple devices.

Pricing and Contracts The newspaper offers multiple subscription options to its readers. The most commonly bought contract is a daily pass, which provides reader access to paid content for one day for €2. The second most common are short term (lasting up to one month) promotional contracts, such as our experimental contracts described below, which are offered to new users who have never been paid subscribers before. Third are regular subscription contracts that continue for an unlimited time until explicitly terminated by the subscriber. The regular subscription prices are €19.99 for the first two months, and €34.99 per month thereafter. Additionally, the publisher has pre-committed (full lock in) 1-year contracts, which are rare.
Canceling subscriptions Users are notified of the subscription terms and conditions and of the technicalities of cancelling before they start their subscription. A subscriber can terminate their subscription at any time, which takes effect in the next billing cycle and the user continues to have access until then. A user can cancel their subscription by calling the publisher’s call center, through the website using the “contact the publisher” page by entering their contract details, or by sending a cancellation letter by mail or email in response to the monthly invoice.\footnote{Overall, the modes of cancellation in our context are very similar to The New York Times, as seen here: \url{https://help.nytimes.com/hc/en-us/articles/115014893968-Terms-of-sale#cancel} (accessed on Jan 11, 2022).}

3 Experiment Design

The field experiment was motivated by our research questions and the publisher’s desire to convert most new users into subscribers of the digital platform via randomized control trials. The experiment was conducted in three phases from April to August 2018, with followup data collected until April 2020.

3.1 Users and Randomization

Any “new” potential subscriber who hits the paywall either by exhausting their quota of free metered articles or by clicking on an always paid article enters the experiment, is randomly assigned to one of eight experimental treatment groups outlined below, and receives the corresponding experimental subscription offer. The newspaper defines a new subscriber as someone who did not pay a full monthly price (€34.99) in the past.

Randomization is induced on the cookie-level and the assigned experimental group persists over time. A balance of the average number of pages visited before hitting the paywall by experimental group is shown in Appendix Table A.1. After the trial period, every user, irrespective of the experimental assignment, has the option to pay the regular amount of €19.99 for the next two months, and €34.99 per month thereafter.

3.2 Experimental Contracts

Our experiment simultaneously varies three factors of the subscription offer. Each factor has two levels leading to a $2 \times 2 \times 2$ experimental design.

1. Subscription Renewal after the Promo: The first factor is the subscription renewal after the end of the promotional trial, which is either auto-renewal or auto-cancellation. A user who takes an auto-renewal promo contract becomes a regular paid subscriber after the trial period is over, by default, unless the user explicitly terminates the subscription. On the other hand, a user who takes an auto-cancel offer does not become a paid subscriber by default. Instead, the user can actively choose to resume the subscription access the next time she hits the paywall, through a pop-up on the platform’s home page, or by clicking on a link in any one of several emails the platform sends the user with an aim of reinstating the subscription.\footnote{Approximately 5 days before the end of the trial offer, an email with a renewal prompt is sent to the user, and a restart of the subscription can be initiated with a click on this email. If a user does not respond to this email, she will be targeted in several follow-up emails as part of the standard process.} In each of these methods, the user verifies her pre-entered payment information and confirms the subscription contract.

2. Duration: The second factor is the duration of the experimental offer, which is either 2 weeks or 4 weeks.

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### Table 1: Experimental offers

<table>
<thead>
<tr>
<th>Experimental group</th>
<th>Renewal</th>
<th>Duration</th>
<th>Price</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>Auto-renewal</td>
<td>4 weeks</td>
<td>€0</td>
</tr>
<tr>
<td>B</td>
<td>Auto-renewal</td>
<td>4 weeks</td>
<td>€0.99</td>
</tr>
<tr>
<td>C</td>
<td>Auto-renewal</td>
<td>2 weeks</td>
<td>€0</td>
</tr>
<tr>
<td>D</td>
<td>Auto-renewal</td>
<td>2 weeks</td>
<td>€0.99</td>
</tr>
<tr>
<td>E</td>
<td>Auto-cancel</td>
<td>4 weeks</td>
<td>€0</td>
</tr>
<tr>
<td>F</td>
<td>Auto-cancel</td>
<td>4 weeks</td>
<td>€0.99</td>
</tr>
<tr>
<td>G</td>
<td>Auto-cancel</td>
<td>2 weeks</td>
<td>€0</td>
</tr>
<tr>
<td>H</td>
<td>Auto-cancel</td>
<td>2 weeks</td>
<td>€0.99</td>
</tr>
</tbody>
</table>

3. Promotional Price: The third factor is price, which is either €0.99 or €0. The price after the experimental offer is identical across individuals, so is the set of contracts from which they can choose one.

The eight combinations of these factors and the corresponding experimental group name are displayed in Table 1. Due to a technical error, users in experimental group G were not required to enter their payment information leading to an invalid experimental condition in experimental phases 1 and 2. This was corrected in experimental phase 3 leading to a full orthogonal experimental design for that phase. We will consider this fact when discussing our results.

#### 3.3 Taking up an experimental offer

From the user’s standpoint, the experimental offer is presented as follows. Upon hitting the paywall, the user is presented one of eight experimental treatment offers in a banner and a reduced teaser version of the article that the reader intended to read. After clicking on the experimental offer, all users have to go through the standard three steps in order to start the trial. First, the user is asked to register and provide an email address and choose a password. Second, the user enters her personal and payment information. Lastly, the user can view the terms and conditions of the selected offer, and click on the check-out button to complete the purchase and enter a legally binding contract with the publisher. Both the email address and payment information are verified before the subscription starts. Importantly, these steps are identical across experimental groups.

### 4 Data

We have two data sources provided by the newspaper. The first is every cookie’s browsing history 14-days prior to being introduced to an experimental treatment and 27-days after leaving the experimental treatment, giving us an observation window of at least 42 days of browsing history per cookie id. The second data are customer relationship management (CRM) data on all subscriptions and contracts, both experimental and regular contracts, from April 2018 to April 2020.

#### 4.1 Usage Data

The browsing history includes each page visited by a reader (identified by a cookie) and timestamp. Other variables are the page type (open, metered, paywalled) and their subscriber identifier if the user was logged in. While all users are tracked for 6 weeks, 14% of users (291,837) are tracked up to 23 weeks.
in to her account (even if not a paying account) at the time of browsing. Most importantly, another variable shows if a reader was exposed to one of the experimental offers on a page visit and to which offer.

Table 2: Summary Statistics

<table>
<thead>
<tr>
<th></th>
<th>Raw</th>
<th>Main</th>
<th>Takers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of users</td>
<td>4,131,277</td>
<td>2,092,846</td>
<td>5,914</td>
</tr>
<tr>
<td>Number of subscribers</td>
<td>36,816</td>
<td>16,339</td>
<td>5,914</td>
</tr>
<tr>
<td>Total revenue (in €)</td>
<td>1,998,352</td>
<td>1,331,719</td>
<td>218,513</td>
</tr>
<tr>
<td>Number of pages viewed</td>
<td>143,628,050</td>
<td>89,177,586</td>
<td>3,128,991</td>
</tr>
<tr>
<td>- open</td>
<td>123,081,315</td>
<td>76,758,421</td>
<td>2,803,811</td>
</tr>
<tr>
<td>- paywalled</td>
<td>14,545,384</td>
<td>8,177,812</td>
<td>201,019</td>
</tr>
<tr>
<td>- metered</td>
<td>6,001,351</td>
<td>4,241,353</td>
<td>124,161</td>
</tr>
</tbody>
</table>

Notes: The table shows summary statistics for the raw data from the publisher, the main data of the users exposed to the experimental offers, and the subset of those who took one of the experimental offers.

From that data we learn a few things. First, we observe and define for each reader their first experimental exposure, and all subsequent exposures. For each reader we use the first exposure as their treatment group and define that date as day 0 of being in the experiment. The number of readers assigned to each treatment group is shown in Figure 1. To keep an intent-to-treat design valid, we define the duration of the different periods in reference to that first exposure date rather than the actual take-up date (if one exists). For example, if a reader in a 2-weeks promo treatment arm saw an offer on April 1st and took that offer on April 8th, the promo period for analysis purposes is 4/1-14 and not 4/8-21. Second, we have information on readers’ usage two weeks before first exposure and four weeks after. That data allow us to compare behavior across treatment arms, and of subscribers and non-subscribers. Finally, we use the data to consolidate multiple cookies associated with the same subscriber, and to consolidate multiple “subscribers” using the same cookie.

After these consolidations we are left with one line for each reader (cookie), which includes their date and type of first experimental exposure, and a unique subscriber identifier if they ever subscribed to the newspaper. We call that the assignment data. There are 2,092,861 readers in the experiment of which 26,196 (1.25%) have a subscriber identifier, and 16,339 of those has a subscription in the two weeks before, or any time after the experiment. Table 2 shows the number of users, subscribers, pages visited, and total revenue. These are presented for the raw data transfered to us from the publisher, the main data used for analysis (for participants in the experiment), and a subsample of participants who subscribed to any of the experimental offers.

Note the common challenge in the digital world, that cookies are not people. However, we know something about the extent of the issue in our setting, and argue that it might shift the effects levels, but not in relative terms. Figure 2 shows the distribution of the number of cookies associated with each subscriber. 63% of all subscribers are associated with only one cookie, and another 18% have two cookies associated with them. While some subscribers regularly clear their cookies, this is a small minority (less than 3% of subscribers have 10 or more cookies associated with them). Yet, the prevalence of multiple cookies per readers who subscribed suggests that non-subscribers will also show up in the data with multiple cookies and might be

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6Some users become subscribers during the time window, while others had a subscription before and are thus identified in the system. However, if a user only subscribed for the first time outside of the usage time window after their exposure, we will not know to link that subscription to the user.
exposed to multiple treatments. Because we cannot defragment different cookies for the never-subscribed, this fact leads to inflation of the number of zeros across the treatment arms. For example, the same reader might have been exposed to several treatments accessing the newspaper from different devices. If they did not take any offer, they would appear as separate users and will contribute “no subscription” and their usage to multiple treatment arms; if instead they did subscribe, then we associate all their devices to the same subscriber with their first exposure determining “day 0” and accumulate all their usage from different cookies together. Therefore, fragmented never-subscribers may lead to compressed subscription shares. However, they do not bias our results since we analyze them in relative terms.

4.2 Subscription Data

The second dataset is the company’s customer relationship management (CRM) data which reports all signed contracts between April 2018 and April 2020 with their revenue, start date, and end date. Each contract is associated with a subscriber identified with a “contractor id” which is the subscriber identifier. The main variable of interest beyond a contract’s start and end time and collected revenue, is the contract code and description. Each of the contracts offered by the newspaper, including the 8 experimental contracts, has a unique code and description. We use these codes to see if readers took an experimental contract or others. Figure 3 shows the distribution of contracts taken by the 16,339 experiment participants who subscribed at any point during the period (another 9,857 had a small subscription before the experiment and did not

\footnote{less than 1.2\% of subscribers have multiple contractor identifiers. We identify those by observing two contractor ids with a shared cookie. That can happen if someone creates multiple users, for example associated with different email addresses. We consolidate those and assign them a single subscriber id.}
choose a new one over these 2 years). A contract is characterized by its maximal potential duration and revenue. The experimental contracts are highlighted with black boxes. As can be seen in the figure, there are many other different contracts being taken and offered. The abundance of possible products matters for the interpretation of results, and we make it clear when we use as an outcome subscription for any contract, experimental or not, or focus on takers of experimental contracts only.

4.3 Merging the Data Sets

Finally, we merge the datasets for analysis purposes. We merge the assignment data with the subscription data to construct at each day, relative to the exposure date, if a reader is subscribed and the average price they paid that day. We then aggregate the days to longer periods as we describe in the next section.

5 Main Experimental Analysis

We begin our analysis by comparing measures of readers’ overall subscription to the newspaper across the experimental groups, by time period. In later sections we analyze the take up of our experimental contracts. Here, our main measures are the user subscription rate, that is, the proportion of days subscribed to the platform through any contract within a period; the user subscription extensive margin, that is, if the user was an active subscriber within that period at all; the revenue attributed to that period; and the numbers of visited pages. For ease of interpretation, we divide our subscription data time span of two years into smaller time periods as follows. We use the two weeks before the promotional period as a placebo to test balance,
Figure 3: Types of contracts taken by experiment participants

Notes: The figure shows shares of contracts taken, characterized by their maximal duration (horizontal axis) and revenue (color). For example, almost half of all contracts are daily passes that cost €1.99. The dark rectangles highlight the experimental contracts—the auto-cancellation contracts are either 2 weeks or a month (4 weeks), and are either free or less than €2; the auto-renewal contracts are indefinite with a revenue above €10.
the first two weeks of the promotional period, the two months of €19.99 price per month, the following two months of the full price of €34.99, and then another three periods of six-months each.

We set up the analysis described below in the form of the following regression

\[ y_i = \alpha + \beta_1 \text{Auto-renew}_i + \beta_2 \text{One-euro}_i + \beta_3 \text{Four-weeks}_i + \epsilon_i, \]  

where \( y_i \) represents one of the outcome measures of individual \( i \)’s subscription, and Auto-renew\( _i \), One-euro\( _i \), Four-week\( _i \) are dummy indicators of \( i \) being assigned to an experimental group with Auto-renewal (as opposed to Auto-cancel), €0.99 (as opposed to free) and four weeks (as opposed to two-weeks) contract terms, respectively. The \( \beta \) coefficients estimate the marginal effects of the experimental factors.

Recall that the experimental group G was incorrectly implemented in phases 1 and 2 of the experiment. So for the main analysis we exclude group G data for consistency across the three experimental phases, and verify that our results do not change when we separately analyze phase 3 data which has all eight groups. Further, since the experimental assignment probabilities varied across experiment phases, we weigh each observation equal to the inverse of the assignment probability so that each experimental group receives the same overall weight. Our empirical results are not sensitive to this.

5.1 Auto-renewal vs. Auto-cancel

Figure 4 plots the intent-to-treat effect of offering a promotional auto-renewal contract as opposed to an auto-cancel contract on subscription behavior at various time periods, which is the estimated coefficient \( \beta_1 \) in equation (1).

Figure 4a shows effects on subscription rates. As expected, the subscription rates prior to the experiment are similar across the experimental groups, so the estimate in the first time bucket is small and indistinguishable from 0. During the promotional time period, we observe a significant negative impact of auto-renewal on subscription rates, which is 28% lower relative to the auto-cancel. Meaning, there are 28% fewer subscription days during the promo period among those offered the auto-renewal versus the auto-cancellation offers. After the promo, however, the effect changes sign, and we see a positive effect of auto-renewal on subscription rate for a few months post promotion. Subsequently, we observe a significant negative trend in the effect and eventually, about a year and a half post promo, the subscription rate is higher for the auto-cancel group. The effect on revenue shows a similar pattern, as seen in Figure A.1 in the appendix, although the revenue effect estimates are less precise.

Comparing these patterns against those in Figure 4b, we note a different pattern on the extensive margin. We do see a negative effect of offering an auto-renewal contract on the likelihood of a reader becoming a subscriber in the promo period. However, we see no positive effect post promo. Fewer readers become subscribers when they receive an auto-renewal offer relative to an auto-cancel in any time period. Overall, we see a significant 9% drop in subscribers over the entire data time period because of auto-renewal.

5.2 Other Experimental Factors

Free vs. €0.99  Figure 5 shows the corresponding effects of changing promo price. The estimates show that increasing the price from free to €0.99 reduces subscription-rate during the promotional time period by 11% and causes 9% fewer readers to subscribe while the promotion was active. As expected, users are more likely to take up a subscription if it costs less. However, this difference fades away over time; we do not observe any effect of the promotional price in any time bucket after the promotion on the extensive margin.
Figure 4: Effect of Auto-renewal relative to Auto-cancel contracts on overall Subscription behavior

Notes: The figures plot the estimated average intent-to-treat effect of offering an Auto-renewal relative to an Auto-cancel contract on consumer subscription behavior. Specifically, we plot the estimated coefficient $\beta_1$ from equation (1) for various time periods. "pre" refers to time before the experiment started; "promo" is the during the promotional time period, the last bucket “ Entire post promo” aggregates across all post promo time periods. Percentages next to the effect size compare the effect to the mean level of the omitted group. The error bars show 95% confidence intervals. Standard errors are clustered at the individual reader level.
or the subscription rate. This implies that increasing subscription trial by decreasing price does not lead to long term subscriptions.

4 Weeks vs. 2 Weeks  Figure 6 shows a similar pattern of the effect of increasing the trial duration. The estimates show that increasing the trial duration from 2 weeks to 4 weeks increases the subscription rate and the number of subscribers by 9%. However, similar to the effect of price, this difference also fades away over time.

5.3 Interpretation

Since our data mostly comprises new users\(^8\), we assume they are uncertain about the value they would get from having the subscription. Additionally, 63% of users in our data visited the website during the two weeks before hitting the paywall and chose to not take up a subscription without the promotion, so their expected value from the subscription is low enough that they would not try the subscription at the regular price.

Our experimental promo reduces the price of trying the subscription, which we assume enables readers to fully resolve their uncertainty. For an auto-cancel contract with a promo price of \(p_0\), the value of taking up the trial is \(v^* - p_0 + \lambda\), where \(v^*\) is the user’s expected value from the subscription during the promo duration, and \(\lambda\) is the future value of the trial which comes through learning the value of the subscription.

Going from an auto-cancel to an auto-renewal promo increases the trial cost for a user who believes an auto-renewal contract will exploit his inertia, that is, the user believes there is a chance \(\iota^* \geq 0\) of him not canceling the subscription in a month post promo even if he does not want it. The total value of taking up the auto-renewal promo is \(v^* - p_0 + \lambda + \sum_{t=1}^{\infty} \iota^t(v^* - p_t)\). Here, \(\iota^t\) is the likelihood of the user being subscribed due to inertia in month \(t\) after the promo end, and \(v^* - p_t\) is the value from having the subscription, which is likely to be negative.

Our findings in Figure 4 show that the users, on average, do differentiate between auto-renewal and auto-cancel and recognize the potential cost due to auto-renewal. Therefore, \(\mathbb{E}\left[\sum_{t=1}^{\infty} \iota^t(v^* - p_t)\right] \neq 0\), and hence \(\iota^*\) cannot be zero across the population.

5.3.1 Calibrating Predicted Inertia \(\iota^*\)

Comparing the estimates of the extensive margin effects during the promo period of \(\beta_2\) and \(\beta_1\) in equation (1) suggests that the average change in the effect of auto-renewal is equivalent to \(2.66 \times\) the average effect of increasing the price by 0.99. Extrapolating linearly, this suggests that the perceived incremental cost of auto-renewal over auto-cancel is €2.64.

Similarly, comparing the estimates of the extensive margin effects during the promo period of \(\beta_2\) and \(\beta_3\) in equation (1) suggests to us that the average perceived value of 2 weeks of paid subscription is equivalent to €0.99 because the estimates of the coefficients are equal. Hence we estimate the average expected value for four weeks of subscription, \(v^* = 2 \times 0.99 = €1.98\).

Hence, in euro terms,

\[-2.64 = \mathbb{E}\left[\sum_{t=1}^{\infty} \iota^t(v^* - p_t)\right]\]

\(^8\)The newspaper defines “new users” as those who did not have a full price subscription before. That is, readers might already had a daily subscription before seeing the promotional offer.
Notes: The figures plot the estimated average intent-to-treat effect of serving a promotional contract costing €0.99 relative to a free contract on consumer subscription behavior. Specifically, we plot the estimated coefficient $\beta_2$ from equation (1) for various time periods. “pre” refers to time before the experiment started; “promo” is the during the promotional time period, the last bucket “Entire post promo” aggregates across all post promo time periods. Percentages next to the effect size compare the effect to the mean level of the omitted group. The error bars show 95% confidence intervals. Standard errors are clustered at the individual reader level.
Figure 6: Effect of 4 week relative to 2 week promotional contracts on overall Subscription behavior

(a) Effect on Subscription rate (proportion of days an individual subscribed)

(b) Effect at the Extensive margin (whether the individual subscribed at all)

Notes: The figures plot the estimated average intent-to-treat effect of serving a 4 week vs. 2 week promotional contract on consumer subscription behavior. Specifically, we plot the estimated coefficient $\beta_3$ from equation (1) for various time periods. “pre” refers to time before the experiment started; “promo” is the during the promotional time period, the last bucket “Entire post promo” aggregates across all post promo time periods. Percentages next to the effect size compare the effect to the mean level of the omitted group. The error bars show 95% confidence intervals. Standard errors are clustered at the individual reader level.
Filling in $p_t$ values gives us

$$-2.64 = \mathbb{E} \left[ (\imath^* + \imath^*2) \times (v^* - 19.99) + \imath^*3 \times \left( \sum_{t=3}^{\infty} t^{\imath-3} (v^* - 34.99) \right) \right]$$

$$\implies -2.64 = \mathbb{E} \left[ 15\imath^* + \imath^*(v^* - 19.99) \right]$$

Assuming no variance in $\imath^*$, and using $\mathbb{E}(v^*) = 1.98$ we can solve this equation and get $\imath^* = 0.126$. Meaning, when making the initial decision to subscribe, a representative reader avoids taking an auto-renewal contract as if he predicts on average a 12.6% monthly chance of failure to cancel the subscription even though he’d wish to.

**5.3.2 Effect of Learning from the Promo Trial**

Increasing the users’ initial subscription rates by reducing price or increasing the trial duration does not significantly change their future likelihood of subscribing to the platform, as indicated by Figures 5 and 6. This finding indicates that the learning from trial experience is not significant enough to change longer term subscription behavior.

Further, comparing the auto-renewal vs. auto-cancel effect with the same effect of price or duration change shows the distinct consumer response to auto-renewal. While auto-renewal causes an average decline in promo take-up, similar to a price increase, it causes an increase in subscription rates post promo, which are absent in response to price increase. At the same time, we see an overall decrease in post promo subscribers due to auto-renewal, which is also absent in response to price increase. These patterns indicate a unique consumer ‘push back’ to auto-renewal relative to more transparent factors such as price and trial duration.

**5.4 Inertia**

In this section, we quantify the degree of actual inertia experienced by users who take up an auto-renewal subscription via two empirical strategies. First, we focus on individuals who take up any of our experimental contracts and compare the likelihood of them continuing their subscriptions post promo between auto-renewal and auto-cancel takers. Second, we compare the differential persistence of the incremental take-up caused by the other experimental incentives (price and duration) post promo between auto-renewal and auto-cancel groups.

**5.4.1 Takers’ post promo subscription behavior**

To fix notation, let $R$ be defined as the set of individual types who take the experimental auto-renewal promo, and set $C$ as the types who take an auto-cancel promo. We assume $R \subseteq C$, that is, individuals who take up the auto-renewal promo would also take the auto-cancel promo, everything else held constant, because the auto-cancel promo offers access to the same content without the risk of an unwanted paid subscription.

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9 Increasing variance of $\imath^*$ from zero gives us similar estimates of the average perceived inertia. For example, if we assume $\imath^* \sim Beta(\alpha,10)$ and is independent of $v^*$, we estimate an $\alpha = 1.3$ which implies $\mathbb{E}(\imath^*) = 0.115$ and $\mathbb{V}(\imath^*) = 0.09$. The assumption of independence of $\imath^*$ and $v^*$ is consistent with our data as shown in later analysis.

10 As discussed in section 5.3, users in our sample chose not to try the subscription at regular price so their prior expected value from the subscription is low. This supports our assumption that they would prefer an auto-cancel contract to auto-renewal which might enroll them into paying for the subscription.
This assertion is supported by our data which shows that promo take-up rate is 64% higher for auto-cancel relative to auto-renewal contracts.

Given this assumption, we can put a lower bound on the average inertia experienced by the individuals in R, that is, the causal effect of auto-renewal on the likelihood of them subscribing post promo. Our rationale is as follows. To estimate the change in subscription behavior of individuals in R when the contract changes from auto-renew to auto-cancel, we need to (1) estimate their post promo subscription when they are given an auto-renewal contract ($y^{AR}_R$) and (2) estimate the same when they are given an auto-cancel contract ($y^{AC}_R$).

Estimating (1) from the data is straightforward because the auto-renewal promo takers are a sample drawn from R.

The observed average subscription behavior of auto-cancel promo takers can serve as an estimate of (2) depending on the behavior of individuals in $C \setminus R$. For example, if individuals in $C \setminus R$ are similar to those in $C \cap R$, then the retention of auto-renew promo takers minus the retention of auto-cancel promo takers can give us an unbiased estimate of the causal effect of auto-renew on long-term subscription.

We believe the users in $C \setminus R$ are likely to be significantly inertial because whether the promo is auto-renewal or not matters to them; these are exactly the readers who would take auto-cancel and not auto-renew and are therefore likely to be concerned about their inertia. However, we can also conservatively assume their post promo subscription rate to be zero and get a lower bound on inertia.

The observed average subscription behavior of auto-cancel promo takers is

$$y^{AC}_C = \frac{|R| \times y^{AC}_R + |C \setminus R| \times y^{AC}_{C \cap R}}{|R| + |C \setminus R|} \geq \frac{|R| \times y^{AC}_R + |C \setminus R| \times 0}{|R| + |C \setminus R|} = \frac{|R| \times y^{AC}_R}{|R| + |C \setminus R|}$$

$$\implies y^{AC}_C \times |C| \geq y^{AC}_R$$

Hence,

$$y^{AR}_R - y^{AC}_R \geq y^{AR}_R - y^{AC}_C \times \frac{|C|}{|R|}.$$ 

We can estimate the RHS of this inequality which serves as a lower bound on the causal effect of auto-renewal on future subscription of users in R.

Table 3 shows estimates from this exercise. The fourth column shows our estimate of the proportion of promo takers who are still subscribed in future months because of the auto-renewal contract term. The fifth column shows our conservative estimate. The table shows significant inertia in our data. The auto-renewal contract causes individuals to subscribe for longer after the promo ends. Fitting an exponential decay function on these estimates yields a conservative estimate $\hat{i} = 0.75$ which is significantly higher than our estimate of the predicted inertia $i^* = 0.126$. 
Table 3: Retention of promo takers

<table>
<thead>
<tr>
<th>Month post promo</th>
<th>(1) Auto-renewal estimate (s.e.)</th>
<th>(2) Auto-cancel estimate (s.e.)</th>
<th>(1) - (2) estimate (s.e.)</th>
<th>(1) - scaled up (2) estimate (s.e.)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>.491 (.014)</td>
<td>.063 (.006)</td>
<td>.428 (.016)</td>
<td>.388 (.017)</td>
</tr>
<tr>
<td>2</td>
<td>.343 (.013)</td>
<td>.049 (.005)</td>
<td>.294 (.015)</td>
<td>.263 (.016)</td>
</tr>
<tr>
<td>3</td>
<td>.264 (.012)</td>
<td>.055 (.006)</td>
<td>.208 (.014)</td>
<td>.173 (.016)</td>
</tr>
<tr>
<td>4</td>
<td>.223 (.012)</td>
<td>.057 (.006)</td>
<td>.166 (.013)</td>
<td>.13 (.015)</td>
</tr>
<tr>
<td>5</td>
<td>.188 (.011)</td>
<td>.055 (.006)</td>
<td>.133 (.012)</td>
<td>.098 (.014)</td>
</tr>
<tr>
<td>6</td>
<td>.168 (.011)</td>
<td>.056 (.006)</td>
<td>.111 (.012)</td>
<td>.076 (.014)</td>
</tr>
<tr>
<td>7</td>
<td>.155 (.01)</td>
<td>.055 (.006)</td>
<td>.1 (.012)</td>
<td>.065 (.014)</td>
</tr>
<tr>
<td>8</td>
<td>.137 (.01)</td>
<td>.053 (.006)</td>
<td>.084 (.011)</td>
<td>.05 (.013)</td>
</tr>
</tbody>
</table>

Notes: The table shows the likelihood of a promo taker subscribing to the platform (even once) in the eight months after the promo ends. Column (1) displays the proportion of promo takers in an auto-renewal experimental group who subscribed to the newspaper in a future month, and (2) does the same for those in an auto-cancel group. The fourth column displays the difference (1)-(2), and the next one does the same after scaling up column (2) by a factor of 1.64 which is the increase in the likelihood of a user taking the experimental promo going from AR to AC.

5.4.2 Using experimental incentives to quantify inertia

In this subsection, we estimate inertia by comparing the differential treatment effects of price reduction and trial duration across auto-renewal and auto-cancel contracts. The rationale is as follows. An experimental incentive—price reduction or an increase in the trial duration—causes some people assigned to an auto-renewal group to take up a subscription during the promo time period. Let $\Delta y_{t}^{AR}$ denote this effect. The proportion of this effect that lasts post promotional time $\Delta y_{t}^{AR} = (\lambda + t') \times \Delta y_{0}^{AR}$, where $t' \times \Delta y_{0}^{AR}$ continue because of the inertia caused by auto-renewal, and $\lambda \times \Delta y_{0}^{AR}$ are those who decide to continue the subscription (e.g., due to them learning that they value it more than the price).

The corresponding effect of the experimental incentives within the auto-cancel group will be similar except that there will be no inertia. Hence, we estimate the effect of inertia in any month $t$ as

$$i_t = \frac{\Delta y_{t}^{AR}}{\Delta y_{0}^{AR}} - \frac{\Delta y_{t}^{AC}}{\Delta y_{0}^{AC}}. \quad (2)$$

In contrast to the approach in section 5.4.1, which estimates average inertia experienced across all auto-renewal takers, this approach estimates inertia experienced by the marginal individuals—those who take an auto-renewal subscription only when an additional incentive is given with it.

Table 4 shows our estimates. For individuals assigned an auto-renewal offer reducing price and increasing trial duration simultaneously, that is, going from 2 weeks, €0.99 auto-renewal to 4 weeks, free auto-renewal increases the likelihood of an individual subscribing during the promo period by 0.0013, which is our estimate for $\Delta y_{0}^{AR}$.

Looking beyond the promo period, in the 4 weeks post promo the difference $\Delta y_{t}^{AR}$ is 53.26% $\times \Delta y_{0}$. This suggests that about half of the immediate increase in subscribers due to the experimental incentives extends beyond the time when the incentives are applicable. Beyond the first month post promo, we see a gradual drop in $\Delta y_{t}^{AR}$, which is detectable up to month 3.

The same incentive for those assigned to the auto-cancel group also increases subscriptions during the promo period by 0.00044, which is smaller relative to the auto-renew group. However, we do not see this

\[11\] For this exercise, we consider the largest increase in incentives within our experiment for most precise estimation of relative increases. Considering only price changes gives similar findings.
Table 4: Effect of experimental incentives on post promo subscription

<table>
<thead>
<tr>
<th></th>
<th>Auto-renewal 4 weeks, Free vs. 2 weeks, €0.99</th>
<th>Auto-cancel 4 weeks, Free vs. 2 weeks, €0.99</th>
</tr>
</thead>
<tbody>
<tr>
<td>Effect in promo time ((\Delta y_0))</td>
<td>estimate (s.e.)</td>
<td>.0013 (.0002)</td>
</tr>
<tr>
<td>Effect post promo month 1 ((\Delta y_1))</td>
<td>.0007 (.0001)</td>
<td>-.00019 (.00013)</td>
</tr>
<tr>
<td>Effect post promo month 2 ((\Delta y_2))</td>
<td>.0004 (.0001)</td>
<td>-.00011 (.00013)</td>
</tr>
<tr>
<td>Effect post promo month 3 ((\Delta y_3))</td>
<td>.0001 (.0001)</td>
<td>-.00010 (.00012)</td>
</tr>
<tr>
<td>Effect post promo month 4 ((\Delta y_4))</td>
<td>-.00018 (.00011)</td>
<td>-.00025 (.00011)</td>
</tr>
</tbody>
</table>

Notes: The first four rows of the table present the effect of changing the promotional terms from (4 week, free) to (2 weeks, €0.99) on the promo period (\(\Delta y_0\)) and post promo (\(\Delta y_t\)) subscription rates, separately for auto-renewal and auto-cancel groups. The next four rows present our estimate of post promo depreciation of subscription relative to promo time. These estimates show that, under auto-renewal, the subscription rate drops to 53% of \(\Delta y_0\) in the first month post promo and is statistically indistinguishable from zero by month 3. Under auto-cancel, the subscription rate drops immediately post promo, and is statistically insignificant in all post promo months. The next four rows present our estimate of the difference in subscription depreciation in auto-renew minus auto-cancel groups. These numbers are large – implying significant inertia – but imprecise because the auto-cancel estimates are large and imprecise.

increase extending beyond the promo time period. If anything, we see lower subscription post promo, which could just be due to imprecision. For the auto-cancel group our estimate for \(\frac{\Delta y_4^{AC}}{\Delta y_0^{AC}}\) is imprecise but significantly lower than the corresponding estimate for auto-renewal group.

Overall, these estimates indicate the presence of inertia on the marginal individuals. However, the \(\iota_t\) estimates are imprecise. If we assume that our imprecise estimates for \(\frac{\Delta y_t^{AC}}{\Delta y_0^{AC}}\) are actually zero, we can see inertia comparable to the average effects in section 5.4.1.

6 Mechanism and Consumer Heterogeneity

6.1 Subscription versus Usage

If the increased subscription caused by auto-renewal is actually unwanted, and caused by inertia, we expect users to get little utility from their post promo subscription. In this section, we use the website usage data to gauge the utility people receive through reading the news articles and empirically assess this explanation.

Using the website usage click-stream data, we estimate the average daily number of pages visited by users who took an experimental auto-renewal or auto-cancel offer. We then compare the trends in subscriptions with those of actual website usage. If auto-renewal takers receive utility from keeping their subscription, we expect their subscription usage, as evident by visits to paywalled pages, to be larger than non-subscribers.

Recall that our usage data spans 6 weeks for each user; if day 0 is the day a user received the experimental offer, our usage data spans days -13 to 27. Figure 7 plots the average page visit and subscription rates data.
Table 5: Usage during vs. post promo for 2 week promo takers

<table>
<thead>
<tr>
<th></th>
<th>Auto-renewal 2 week €.99 subscribers</th>
<th>Auto-Cancel 2 week €.99 subscribers</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Subscribed in two weeks post promo</td>
<td>Not subscribed in two weeks post</td>
</tr>
<tr>
<td></td>
<td>estimate (s.e.)</td>
<td>estimate (s.e.)</td>
</tr>
<tr>
<td>Promo 2 weeks: Avg. page visits</td>
<td>25.37 (3.66)</td>
<td>22.28 (2.64)</td>
</tr>
<tr>
<td>Promo 2 weeks: % users with any visit</td>
<td>0.78 (0.04)</td>
<td>0.68 (0.04)</td>
</tr>
<tr>
<td>Post promo 2 weeks: Avg. page visits</td>
<td>20.33 (3.57)</td>
<td>12.88 (2.92)</td>
</tr>
<tr>
<td>Post promo 2 weeks: % users with any visit</td>
<td>0.49 (0.04)</td>
<td>0.43 (0.04)</td>
</tr>
<tr>
<td>N</td>
<td>134</td>
<td>136</td>
</tr>
</tbody>
</table>

Notes: We focus on the users who took the 2 week, €.99 experimental contract and separate them by (1) whether they took the auto-renewal or auto-cancel contract and (2) whether they were subscribed in the two weeks post promo. The first two rows present the average number of page visits, and the proportion of users who had any visit to the newspaper in the first two weeks. The next two rows do the same for the subsequent two weeks. The results show that, on average, the auto-renewal contract takers who are still subscribed after the promo period use the newspaper with the same intensity as those who did not subscribe; their usage is lower than those in auto-cancel who subscribe post promo.

among promo takers for each day in this time span. For this plot, we use data for individuals who took either a 2 week, €0.99 auto-renewal promo or a 2 week, €0.99 auto-cancel promo during the first days after exposure, so we can observe the promo time ending in the middle of our 4 weeks post treatment usage data.

Figure 7 shows that auto-renewal promo takers are far more likely to be subscribed after the 2 week promo time, relative to auto-cancel subscribers. However, we do not see any difference in their website visits. This indicates that the auto-renewal takers who continue to subscribe do not visit the website more often. Compared to pre-treatment days, we see that both groups use the website more post promo take up.

Table 5 shows promo and post-promo usage statistics averaged across users who took either a 2 week €0.99 auto-renewal or auto-cancel promo. The sample is grouped by whether the user was also a subscriber post promo, or not. The analysis shows that more than half of the users who subscribed in the two weeks post promo after taking an auto-renewal promo did not even visit the newspaper’s portal. This proportion is similar to those that did not subscribe post promo and is significantly lower than those who subscribed post promo after taking an auto-cancel offer.

Overall, this analysis is consistent with our inference that the users who continue subscribing after taking an auto-renewal promo do not derive higher utility than those who do not.

6.2 Distribution of Consumer Sophistication

We assess the distribution of consumer sophistication-types using our promo take up and subscription data. First, we estimate the size of the population who may be interested in taking up any experimental promotion as those who take the best auto-cancel offer (4 weeks for free). We use the size of that group as the baseline population whose sophistication our data can assess. This step is important because a large proportion of the readers who are shown an experimental promo when they hit the paywall do not click on it, so their sensitivity to auto-renewal is not estimable. We operate under the assumption that auto-cancellation, 4 weeks, and free are preferred over auto-renewal, 2 weeks, and €0.99 promo terms respectively. Meaning, we assume that any reader who takes, for example, a 2-weeks contract will also take a 4-weeks contract all else equal.

We estimate those who avoid taking the promo because of its auto-renewal nature by contrasting the
Figure 7: Subscription vs. Platform usage for 2 weeks, €0.99 auto-renewal promo takers vs. 2 weeks, €0.99 auto-cancel promo takers

Notes: The figure plots the daily average subscription rate (dots and triangles) and average newspaper consumption—measured by number of website page visits (bars)—separately for those who took the 2 week €0.99 auto-renewal promo and those who took the 2 week €0.99 auto-renewal promo. The time on the x-axis starts 2 weeks before the experimental offer was given to the user and covers the promotional 2 weeks and 2 weeks after that.
auto-renewal with auto-cancel promo take up. We estimate “always takers”—those who would take up a subscription irrespective of the experimental promo terms they receive—as the lowest share of subscribers post promo across treatment arms (effectively, these are the auto-cancellation subscribers).

The remaining population takes up an auto-renewal promo but either (1) manages to unsubscribe before renewal, in which case we label them as sophisticates, or (2) cancel within the subsequent three months (partial sophisticates), or (3) does not cancel until then, in which case we label them naives.

These labels follow the literature convention of signifying the degree to which consumers realize their future limitation and act to avoid getting penalized, which in our context arises due to the inertial consequences of taking an auto-renewal offer. Figure 8 shows this distribution. Among the population interested in our experimental promo, 1% are always takers; 36% are able to recognize the auto-renewal promo term and avoid taking it; an additional 33% take up the auto-renewal promo but act within the trial period’s deadline and cancel before the promo ends; 19% continue the subscription for three months and cancel then; lastly, 10% exhibit naivete by not canceling up to three months post promo.

Overall, this distribution indicates that about 70% of the interested population is sophisticated enough to not overlook the consequences of the auto-renewal contract term.

6.3 Targetability based on Sophistication

Is it possible to target users with offers based on their sophistication? Is user sophistication predictable? We use our pre-experimental usage data—which includes the topics the users browse—to predict the heterogeneity in the effects of our treatments. While we find some predictors of higher usage, these do not translate to differential treatment effects. Since we do not find predictable differential treatment effects, our data is unable to predict sophistication. This is exhibited in Figure 9. The figure shows the auto-renewal vs. auto-cancellation treatment effects based on type categorization into “high” and “low.” There is no predictable heterogeneity between the types.

To categorize types, we use data on usage each day before the experiment to predict if a user attempted to read any paywalled or metered article during 1 to 4 weeks after entering the experiment. Specifically, as predictive variables, we use the number of always open, metered, and paywalled pages on each of the 13 to 1 days before hitting the paywall (total of 39 continuous variables) as well as the type of paywall users hit eventually when they entered the experiment (metered or always-paywalled content), as inputs to a Random Forest algorithm, cross-validated with a 10-fold procedure. We then reran the main analysis fully interacting the treatment with these predicted types.

We also investigate the ability to identify observed characteristics that would predict consumer preference for the auto-renewal option. Presumably, those who would like to be long-run subscribers would rather subscribe only once, rather than having to renew once the promo period ends. However, we are not able to find a user segment that would prefer auto-renewal over auto-cancel.

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12 We tried different methods to ensure that the unpredictability we find is not due to our modeling choice. We used predicted usage levels rather than any usage, changed the time window of what is considered post-usage, and used pre-experiment usage to define types (regardless of post-usage). The results are similarly noisy and indistinguishable between the “low” and “high” types however we cut the data.
Figure 8: Description of heterogeneity in consumer sophistication among those interested in the experimental promo.

Notes: 100% here is the proportion of the population that takes up the most popular experimental promo. “Avoiders” are the proportion of auto-cancel takers who decide not to take an auto-renewal promo. “Always takers” have a subscription in the longer term after taking an auto-cancel promo. “Early cancelers” are those who take up an auto-renew offer but cancel before the promo ends. “Late cancelers” are those who cancel after the promo ends but within 2 months. “Naives” are those who do not cancel up to that time.
Figure 9: Auto-renewal effects by types of readers

Notes: The figure shows the ITT effects of auto-renewal separating readers into types based on their predicted usage given their pre-experiment usage. High types are those predicted to be at the 5% of most engaged readers, low types are the bottom 95%.
6.4 Discussion

6.4.1 Further evidence against cost-benefit driven inertia

We now turn to investigate the channels behind inertia. The difference in take-up means that readers predict their future inertia, ruling out myopic switching costs; perfect foresight of switching costs predicts similar subscription levels after the promo, which is also ruled out. Another alternative is that consumers have stochastic switching costs and are therefore waiting for an opportune time to cancel their subscription. We argue against that model with two exhibits.

First, if our findings reflect consumers who make an active and calculated choice to not leave the auto-renewing contract due to fluctuating switching costs, then this cost-benefit analysis must change when the price changes. Concretely, consumers might be willing to remain subscribed for €19.99 per month, but some should respond to the price increasing to €34.99 before that change. However, the response is muted, and indistinguishable from periods without any price changes. Figure [10] shows the month-over-month hazard rates of takers of auto-renewal contracts. The hazard on month 3, when the price increases by €15, is 23.8%, implying a naive semi-elasticity of -1.59% per €1. However, two comparisons suggest this is a small number. First, the hazard is only somewhat higher than month 4 and lower than month 2, two adjacent months for which there were no price changes (implying infinite concurrent semi-elasticity). These are meaningful. If consumers are making an active choice every month, those who are willing to pay €19.99 but not €34.99 should mostly leave on month 3 preemptively but not before and not after. If, in contrast, consumers are largely inert and inattentive, then those who were not willing to pay even €19.99 but remained subscribed are slowly trickling away on each of these months. But this in turn implies that most of the 23.8% are not attributed to the price increase, thus implying a much smaller response due to the price change. Second, the experimental estimates for the price effect (free promo vs. the €0.99 promo) imply an ITT semi-elasticity that is 5.7 times larger (-9% for a €0.99 price increase), and the promotional price effect among auto-renewal takers implies a semi-elasticity that is 23.2 times larger. Thus, we find a small response to the price increase on the third month compared to months without price changes and to the price of the promotional weeks.

This lack of response to the price change suggests strong inertia that is not due to cost-benefit analysis—whether known hassle costs, myopic and fixed costs, or variable costs—but due to consumers being mostly passive and only occasionally act. They do not act as a response to incentives, but randomly so.

6.4.2 Evidence for “spite”

The average subscriber types at different periods speak to the mechanism driving our estimated effect of serving an auto-renewal vs auto-cancel contract. Assuming that consumers with higher valuation of the product are more likely to subscribe, we expect the average type of auto-renewal subscribers to be higher than auto-cancellation subscribers during the promo period because the marginal reader that does not take an auto-renewal will take an auto-cancellation promo. However, after the promotional offer ends, auto-cancellation subscribers are those who actively subscribe while the large share of auto-renewal subscribers remain due to inertia. Meaning, after the promotional period, the average type of auto-renewal subscribers should be lower than for auto-cancellation subscribers. Over time, irrespective of whether users are being driven by switching costs (standard or coupled with present-bias) or random attention as described above, we should expect the types to converge from below in the long run.

\[ \text{The effect on takers only is } -37\%. \text{ It is calculated as } \frac{S_{AR}^{0.99} - S_{AR}^{0.99}}{S_{AR}^{0.99}}, \text{ where } S_x \text{ is the share of experimental offer takers among those exposed to an offer with price } x. \]
We find support for the former two predictions but not for the latter. We use the pre-experimental usage data to predict post treatment usage for each user in our data. We use this predicted usage as a proxy for the user’s type – those who are predicted to use the newspaper more are higher types. Figure 11 shows the by-period difference in user types between auto-renewal and auto-cancellation subscribers. The promo period subscribers in the auto-renewal group are of higher types relative to the promo period subscribers in the auto-cancel group. In the initial periods after the promo ends, lower types subscribe in the auto-renewal group (yet not significant at the 10% level), but the difference then flips sign and becomes larger again in the long-run.

These findings show that, in the long-run, users who choose to subscribe in the auto-cancel group decide not to subscribe when assigned to the auto-renewal group. This implies that auto-renewal is deters even those who wish to remain subscribed. Note that the contracts offered to both groups are equivalent in the long term; unlike the promotional period where the auto-cancellation contract has a different continuation value, after the promo period all contracts are identical. This pattern is consistent with a psychological cost or spite against the newspaper due to the initial auto-renewal offer. This finding is consistent with the extensive margin result of fewer subscribers after the promo period (shown in section 5), and it further suggests that some of these missing subscribers are high value subscribers.

6.4.3 Firm’s incentive

The common knowledge in the academic literature as well as in the industry is that consumers are highly inert. Once a firm gained a consumer, the argument goes, the firm can increase prices or change terms and the consumer is insensitive to those. A large body of evidence, including this paper, supports the view that
existing consumers are highly inert. However, this body of knowledge relies on a selected sample of already existing customers. Our paper suggests that a large portion of customers, between 24% and 36%, is aware of its future inertia and avoids engaging with an exploitative contract. Furthermore, offering an exploitative contract pushes 9% of customers from engaging with the company in its entirety for the duration of our data. These new findings imply that consumers’ awareness to their future inertia limits inertia exploitation.

In our setting, if the firm’s horizon is a few months of profits, then indeed offering an auto-renewal contract would have been beneficial. However, if longer term profits matter, then there is no benefit for the auto-renewal contract. By the half-year following the first 4 months, the revenue difference is statistically indistinguishable from 0, and the differences get smaller as time goes by. Furthermore, if the market share, or size of readership matters, then auto-renewal is worse from day 1. There are various reasons why readership matters, such as advertisement revenue, or the potential for word-of-mouth and social media engagement to expand readership further. Finally, as our usage analysis suggests, those who remain subscribed due to the auto-renewal nature of the contract do not use their subscription, meaning that the contract is indeed exploitative and does not bring value to consumers. Overall, at the medium and long run, if the firm can only choose one type of contract to offer, auto-cancellation contracts seems like a Pareto improvement for the firm and consumers.

In theory, the firm might be able to benefit from “sophistication discrimination.” Either by offering different readers different contracts based on their naivete, as in a third-degree price discrimination, or by designing a contract menu to exploit naivete (e.g., Eliaz and Spiegler (2006)). In our setting, targeting based on naivete seems limited in scope, as we were not able to find predictive features. Further, while the newspaper already offers a host of contracts, including some not exploitative such as a one day pass, our

Notes: We use the pre-experimental usage data to predict post treatment newspaper usage, which we use as a proxy for user type. The figure shows the difference in average user type between subscribers in the auto-renewal group and auto-cancellation group by period. Error bars are 95% confidence intervals, and the light gray sections represent 90% confidence intervals. For example, during the promo period the subscribers in the auto-renewal group are significantly higher types compared to the subscribers in the auto-cancellation group. Standard errors are clustered at the individual level.
results suggest that the mere offer of an exploitative contract as part of the menu deters some consumers from participation. This notion, of consumers making inference about the firm from the set of contracts it offers, should be taken into account in contract design.

7 Conclusion

We design a large-scale experiment that enables us to study inertia in consumer subscription decisions. The novel experiment design simultaneously varies the contract renewal terms along with other benefits, which allows us to quantify the inertia consumers anticipate from taking up the subscription, before they actually take it. Their subsequent subscription behavior enables us to quantify the actual inertia they experience. Overall, we find that consumers do recognize and account for their inertia, but they underestimate it by a factor of six. About 30% of the consumers take up the auto-renewal subscriptions and end up paying for the subscriptions they do not want. Overall, in the long term, consumers behavior disincentivizes the newspaper to present auto-renewal offers, even though auto-renewal leads to higher firm revenue in the medium term because of inertial subscribers.
References


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## A More Results

Table A.1: Balance of pre-experiment behavior

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<th>Dependent Variables</th>
<th>Total Pages</th>
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**Fit statistics**

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**Notes:** Heteroskedasticity-robust standard-errors in parentheses

Signif. Codes: ***: 0.01, **: 0.05, *: 0.1
Figure A.1: Revenue rate when Auto-renewal contracts are served relative to Auto-cancel contracts

Notes: The figure plots the estimated average intent-to-treat effect of serving an Auto-renewal relative to an Auto-cancel contract on the newspaper’s revenue. Specifically, we plot the estimated $\beta_1$ from equation (1) for various time periods. “pre” refers to time before the experiment started; “promo” is the during the promotional time period, the last bucket “Entire post promo” aggregates across all post promo time periods. The error bars show 95% confidence intervals of the $\beta_1$ coefficient.
Figure A.2: Subscription Levels when Auto-renewal contracts are served relative to Auto-cancel contracts

(a) Subscription rate (proportion of days an individual subscribed)

(b) Extensive margin (whether the individual subscribed at all)

Notes: The figures plot the levels along with estimated average intent-to-treat effect of serving an Auto-renewal relative to an Auto-cancel contract on consumer subscription behavior. Specifically, we plot the estimated $\alpha + \beta_1$ from equation (1) for various time periods. “pre” refers to time before the experiment started; “promo” is during the promotional time period, the last bucket “Entire post promo” aggregates across all post promo time periods. The error bars show 95% confidence intervals of the $\beta_1$ coefficient.