Promoting Rule Compliance in Daily-Life: Evidence from a Randomized Field Experiment in the Public Libraries of Barcelona*

Jose Apesteguia Patricia Funk Nagore Iriberri†

February 2011

Abstract

We study how to promote compliance with rules in everyday situations. Having access to unique data on the universe of users of all public libraries in Barcelona, we test the effect of sending email messages with different contents. We find that users return their items earlier if asked to do so in a simple email. Emails reminding users of the penalties associated with late returns are more effective than emails with only a generic reminder. We find differential treatment effects by user types. The characteristics we analyze are previous compliance, gender, age, and nationality.

Keywords: Rule Compliance, Field Experiment, Public Libraries.

JEL classification numbers: C93, D01, D03, D63, K42.

*We are grateful to Anna Surroca (*Serveis de Biblioteques of the Diputacio de Barcelona*), Judit Terma (*Consorci de Biblioteques de Barcelona*), and their respective teams, for their collaboration and assistance in conducting this study. We thank Antonio Cabrales, Pablo Casas, Vincent P. Crawford, Uri Gneezy, Rosemarie Nagel, Imran Rasul, Pedro Rey-Biel, Carmit Segal and Christian Traxler for helpful comments. Special thanks go to Stephan Litschig for constant feedback and discussions. Sergio Correia provided excellent research assistance. Financial support from the Spanish Commission of Science and Technology (ECO2008-01768, ECO2009-12836, ECO2009-11213 and SEJ2007-64340), Fundación Rafael del Pino, the Barcelona GSE research network, and the Government of Catalonia is gratefully acknowledged.

†Universitat Pompeu Fabra and Barcelona GSE. E-mails: jose.apesteguia@upf.edu, patricia.funk@upf.edu, and nagore.iriberri@upf.edu.

1 Introduction

Understanding compliance with rules is crucial for modern societies. No matter whether we talk about littering on the streets, picking up children from the kindergarten on time, or appropriate behavior in public places like metros or libraries, learning about effective tools for promoting compliance with rules is of obvious importance. While economists would naturally think about monetary incentives, it has been found that they may backfire (see Benabou and Tirole, 2003 and 2006, for theoretical arguments; Gneezy and Rustichini, 2000, and Mellstroem and Johannesson, 2008, for empirical studies), or that they are not feasible due to political and institutional restrictions. Therefore, it is crucial to understand whether there are other possible ways to promote compliance with rules. The goal of this paper is to analyze the effect of conveying various types of messages, in our case by email. Our interest in the potential effects of sending messages is that it offers a virtually costless and non-invasive intervention mechanism that is simple to implement and very flexible for our, as well as for other applications. Surprisingly, despite the advantages of this message intervention, little is known about its effectiveness.

The setting that allows us to study compliance with rules on a large scale is the Network of Public Libraries in the city of Barcelona. The type of compliant behavior we analyze is whether users of the libraries return the items they borrowed on time. A user not returning an item by the due date is violating the rule, and generating a negative externality on the population of users. We evaluate whether we can get users to return the items they borrow earlier; by means of different email contents that are randomly allocated.

Our study will be informative for the optimal design of message contents in any setting where compliance with rules is desired. As an illustration, in many countries, the driving authorities convey messages to drivers by way of electronic panels in the roads, with the aim of promoting careful driving. Such messages, for example, include reminders of the penalties associated with breaking driving rules, or reminders of the possible impact of one's behavior on others. However, the effect of these messages is, to the best of our knowledge, unknown. The study of the behavior of library users contingent on different message contents will improve our understanding on the effectiveness of such a mechanism, and serve as a basis for the design of future message interventions in other settings of interest.

There are important characteristics that make our study unique. First, we observe the behavior of all users of all public libraries in Barcelona over eleven months. During this time span, there were about 50,000 different users, who borrowed over a million items in the 32 different libraries spread throughout the city of Barcelona. Therefore, we have data on a large number of individuals, in a daily-life situation, taking part in their natural environment, and over an extended period of time. Second, we observe *every* borrowing-returning transaction of items made by users. This allows us to measure compliant behavior with exact precision. In other words, we are able to determine precisely when individuals conform with the rule and when they violate it, and if so, how severe these violations are. Third, the rules that govern the interaction between the users and the libraries are simple and well-defined. In particular, the penalty associated with returning an item late does not involve any monetary fines, but the exclusion from the possibility of borrowing more items for a time period equal to the number of days the item is overdue. Finally, the rich data on users offers a unique opportunity to test for differential treatment effects depending on important demographic variables, such as gender, age and nationality.

We randomize all users into groups receiving one of five different email messages, and study their behavior after receiving the email. One of the five email messages is a Control message that provides a link to the webpage of the Network of Libraries.[1] All the remaining messages add content to the text in Control. The first treatment message, called Reminder, represents a general reminder of the users' duty to return the borrowed items on time. The second message, Social, adds to Reminder an appeal to the effect individual behavior can have on the overall functioning of the public library services, besides pointing out its importance. The last two email treatments, Late and Penalty, are targeted only at those users who have recently returned at least one item late. Both Late and Penalty add to Reminder the identification of the user as having recently returned items late. Finally, Penalty builds on Late and adds a reminder of the penalty associated with non-compliant behavior.

These email treatments allow us to evaluate the impact of different message contents

[1] The idea is that by comparing the effect of the treatment messages relative to the control, we are able to differentiate between the effect of the content of a treatment message and that of just getting an email from the Network of Libraries.

on users' behavior. Reminder is a clear call to the duty of users to comply with the rule. Social adds a justification to the users' duty that appeals to the social good aspect of the Public Libraries. Late identifies users as non-compliants and Penalty points to the private consequences of being late. Therefore, we can test whether contents appealing to the social problem of returning an item late are more effective than a generic reminder to return the borrowed items on time, or, similarly, whether being identified in an email as a recent non-complier is more effective than a generic reminder.

Given our design, we study the effect of email treatments on all users, independent of whether they were initially complying with the rule or not, by comparing Control, Reminder and Social; and the effect on previous non-compliers by comparing Control, Reminder, Social, Late and Penalty. Note also that we send messages to all users who have been using the library services, independent of whether they have an item or not borrowed at the time of the intervention. We chose so in order to to be as general as possible in our design. Clearly, if the message intervention not only affects current, but also future users, its impact is more far-reaching.

In our analysis we evaluate the effect of emails on the proportion of late returned items by user, and on the number of days that elapse between the return date and the due date. The first variable measures the propensity to comply with the rule, while the second variable measures the positive/negative externality that is imposed on other users when a user returns the item earlier/later than the due date.

Our main result is that compliant behavior can be promoted by sending a simple email. All emails significantly reduce both, the proportion of late returned items, and the number of days between the return date and the due date. The greatest effect comes from the Penalty treatment, reducing the proportion of late returned items by 10 percent, which has a significantly greater effect than the 5 percent reduction of the general Reminder. The effects are not only statistically significant but also economically relevant, especially in light of the negligible costs associated with the intervention.

As for the effectiveness over time, we show that the effect of getting one of these emails is short-term; the effect is significant during the first month after the email intervention, but not afterwards. However, the effect is reproduced when the same email is received for a second time, in our case two and a half months later. As such, our results suggest that sending multiple emails can help to keep compliance high.

Our data also allow us to study the effects on behavior by user-type. Regarding previous compliance, we find that users with a higher proportion of late returns in the pre-treatment period react more strongly than users with a lower proportion of late returns. Interestingly, even the "good citizens" react positively to receiving an email. Hence, the email treatment is more effective precisely with those users whose compliance prior to the treatment was lower, and, importantly, does not generate crowding-out effects in those users that were complying with the rule before the intervention. We also find different effects by age groups. For example, we show that users under the age of 20 do not react to any email content in terms of the proportion of late items per user, while users in the age classes 20 to 40 and 40 to 60 are generally responsive to receiving the emails. Users between 40 and 60, and over 60 seem to react mainly with regard to the Penalty treatment. With respect to gender, our results show that there are no significant differences in reactions to the treatments between women and men. Finally, there are wide variations that depend on the users' nationality. We study reactions of users from Spain, Northern-Central Europe, Western and Southern Europe, English speaking countries (UK, USA, CA), East Europe and Russia, Latin America and Asia. Interestingly, only Spaniards, people from English speaking countries and Asians react to the emails. We then evaluate whether Asians or citizens of English speaking countries react differently to the treatments than Spaniards do. Here, we see that users from English speaking or Asian countries react much more strongly than Spaniards. For example, Spaniards reduce their propensity to be late by 10 percent after having received a Penalty message, while citizens from English speaking countries reduce their propensity to be late by 43 percent for the same message type.

Our results relate to different strands of literature. Most directly, our study fits into the growing literature on how to promote pro-social behavior and compliance with rules.[2] There is evidence that visibility of good/bad behavior may induce compliant/pro-social behavior due to social sanctions and social rewards (Gerber, Green, and Larimer, 2008; Funk, 2010). Also, allowing for free communication between interacting agents before they take actions has proven to change outcomes in specific experimental settings

[2]While pro-social behavior usually refers to actions that mainly benefit others, compliance with rules involves elements of pro-social behavior if the penalty is small. In our case, returning items on time most likely involves both, compliance with rules and pro-social behavior.

that broadly relate to pro-social behavior, such as hold-up problem games (Ellingsen and Johannesson, 2004), trust games and hidden-information games (Charness and Dufwenberg, 2006; 2010) and dictator games (Ellingsen and Johannesson, 2008; Andreoni and Rao, 2010). However, relatively little is known about the effect of *specific message contents* on promoting pro-social behavior and compliance with rules. Relevant exceptions to the latter are Schultz et al (2007), Ayres, Raseman and Shih (2009), Karlan et al (2011), Dal Bó and Dal Bó (2009) and Fellner, Sausgruber, and Traxler (2009).

Schultz et al (2007) and Ayres, Raseman and Shih (2009) show that home electricity consumption can be reduced when households get periodic reports on the consumption of comparable neighbors. An important difference between these studies and ours is that in our case there is a clear rule that dictates what to do, namely to return the items on time, as opposed to the unwritten, informal norm of not over-consuming electricity. Karlan et al (2011) show that when individuals are reminded of their previous saving commitments, the likelihood of reaching their saving goal increases. The main difference with our setting is that in Karlan et al (2011), individuals self-impose to a saving rule, with no punishment associated for breaking it. Dal Bó and Dal Bó (2009) conducted a series of laboratory two-player public good experiments to study the influence on individual contribution levels when players receive a message appealing to moral rules. They showed that receiving a message with a moral standard increases contribution levels, although the effect is transitory. Again, our study involves a setting with a clearly defined rule, as opposed to an unwritten social norm, and furthermore, it involves a field experiment that studies the effect of sending messages in a natural environment. Fellner, Sausgruber, and Traxler (2009) study the effect of different mailings to potential evaders of TV license fees. They find that a legal threat mailing significantly increases compliance rates, while neither a moral appeal nor a social information mailings have any effect. The main difference to Fellner, Sausgruber, and Traxler (2009) is that we can measure compliance and non-compliance perfectly and study the effect of messages on these different types of behavior. Furthermore, our data on user characteristics allow us to study differential effects with regard to gender, age and nationality. Finally, their setting and ours also differ in terms of the associated penalties for non-compliance. While in their case these are very high, in ours they are relatively minor.

Our findings are also relevant for a growing literature that investigates gender differences in preferences and behavior (e.g. Andreoni and Vesterlund, 2001; Charness and Gneezy, 2007; Charness and Rustichini, 2009; Croson and Buchan, 1999; and Niederle and Vesterlund, 2007; see Croson and Gneezy, 2009, for a comprehensive and exhaustive survey). Evidence on gender differences in social preferences, altruistic behavior and cooperation seems to be mixed. Croson and Gneezy (2009) suggest that this is likely to be due to women being more sensitive to the experimental context than men. Our study complements this literature by studying gender differences on rule compliance in an everyday and natural situation (see Levitt and List, 2007). We find that there are no significant differences by sex in reactions to the email intervention.

Finally, our paper is also relevant for a strand of literature that investigates the effects of culture on behavior. There is evidence that culture matters in a variety of outcomes, such as labor force participation and fertility (Fernandez, 2007a; Fernandez, 2007b), economic exchange (Guiso, Sapienza and Zingales, 2009), redistribution (Luttmer and Singhal, 2010; Fong and Luttmer, 2009), cooperation (Herrmann, Thöni and Gächter, 2008; Gächter, Herrmann and Thöni, 2010), and, most related to our study, violations of rules (Fisman and Miguel, 2007).[3] Our study is consistent with Fisman and Miguel (2007) in that there are major differences in compliant behavior by individuals with different countries of origin. To start with, we find that Asian people comply with rules more than other nationalities. Also, they react quite strongly to receiving emails, together with people from English speaking countries. Finally there are groups of countries (Western-Southern Europe, Russia, Latin America), where compliance is poor to begin with, and there is little reaction to receiving emails from libraries.

The remainder of this paper is organized as follows. Section 2 describes the setting, namely the Network of Public Libraries in the city of Barcelona, and explains in detail the design of the field experiment, as well as the identification strategy. Section 3 is devoted to the presentation and discussion of the results. Finally, Section 4 presents conclusions.

[3]Fisman and Miguel (2007) study parking violations by diplomats in New York City. Since diplomats could not be fined due to diplomatic immunity, the setting allowed the analysis of which nationalities were more likely to break rules in an environment of zero punishment.

2 The Field Experiment

2.1 The Setting: Network of Public Libraries of Barcelona

The Network of Public Libraries in the city of Barcelona is managed by a central body dependent on the City Hall of Barcelona and the Government of the Province of Barcelona. It encompasses 32 libraries spread throughout the city of Barcelona. Each library offers the possibility of borrowing items such as books, DVDs, CDs and magazines; other services such as internet access, exhibitions and workshops are also provided.

The rules governing the borrowing of different item types are clearly defined and are the same for all the 32 libraries. At the time of our study, a book could be borrowed for 21 days, while all other item types (DVDs, CDs and magazines) could be borrowed for 7 days. Users could also explicitly ask to extend the due date if no other user required that item. As for the maximum number of items to be taken, each user could simultaneously take a total of 30 items, 15 books and magazines, and 15 CDs and DVDs. The penalty associated with returning an item late involved being barred from borrowing new items for a time period equivalent to the number of days elapsed between the due date and the actual return day. In particular, there was no monetary fine associated with not complying with the return policy.

2.2 Data

We observed the complete borrowing/returning behavior for every single user at the Network of Public Libraries of Barcelona from January 2009 until the beginning of November 2009. This included any user at any of the 32 public libraries in Barcelona. For every transaction we observed (i) the user code, gender, age, and nationality, (ii) the item code and its characteristics, that is, whether it was a book, DVD, CD, or magazine, (iii) the dates of the transaction, that is, the date when the item was borrowed and returned, and (iv) the library where the transaction took place. With this information we were able to follow the exact borrowing behavior of every single user of the Network of Public Libraries in Barcelona. Given that our design is based on emails, we concentrate on the sample of those users with a known email.[4] This gives

[4]The Network of Public Libraries knows the email addresses of about 40% of the registered users.

us about 50,000 different users, who borrowed over a million items.

The data set encompasses a diverse set of users in terms of individual characteristics (age, gender and nationality), but also in terms of their borrowing behavior. In particular, we observe the type of items they borrow (books, or other item types), whether they are compliant or not, as well as whether they are persistent late returners. Furthermore, libraries also present significant differences in terms of their size, both in terms of number of users and number of transactions, location and proportion of late returners.

2.3 Email Contents

The Network of Public Libraries in the city of Barcelona maintains constant communication with its users via email. Most emails include information on the activities organized in the different libraries of the city, such as exhibitions or workshops, and on opening hours. In collaboration with the Network, we designed five different email messages (see Table 1) that were randomly assigned to the users. The objective of the study is to evaluate the impact of these messages on users' behavior.

[Table 1 here]

As can be seen from Table 1, CONTROL refers to the control treatment. It provides a link to the webpage of the Network of Public Libraries in Barcelona. The rest of the treatment messages build on CONTROL, adding different pieces of information. REMINDER represents a general reminder to return items on time. Note that this general reminder (and the other treatments as well) do not include any reference to particular items that were borrowed at the time of receiving the email. Therefore, it can be directed to all users, regardless of whether they had borrowed any item at the time of receiving the message. SOCIAL builds on REMINDER, incorporating a moral and social dimension. It adds an appeal to the influence of individual behavior on the proper overall functioning of the public system of libraries. These two emails, REMINDER and SOCIAL, together with CONTROL, were designed to target any possible user, regardless of whether the user had returned some items later than the due date in the recent past. The final two emails were specifically designed to target users with late returns in the recent past. Email LATE adds to the content of REMINDER a statement that identifies the user as having recently returned an item late. Finally, PENALTY builds on LATE adding a reminder of the actual penalty associated with returning an item late.

In our analysis, we will compare the effect of receiving a REMINDER, SOCIAL, LATE or PENALTY email, with that of receiving CONTROL. That is, we will study whether any of the four treatments improves with respect to a CONTROL message. Furthermore, the contents of the emails potentially allow us to distinguish between different motives for behavioral changes. For example, the difference in the texts between REMINDER and SOCIAL allows us to evaluate whether appealing to the importance of one's contribution to the good functioning of a public service is more effective than a generic reminder. Comparing LATE with REMINDER is useful to test whether being identified as non-compliant with the rule has a different effect than the generic reminder. Finally, PENALTY allows us to test for any differential effect of recalling the penalties associated with violation of the rule.

It was our aim to design emails with general contents that could be applied to many settings of interest beside libraries. For this reason, no email makes any reference to particular items that may have been borrowed at the time of receiving the email. Also, we kept in mind that not all settings permit the type of precise data on individual behavior that we had at the moment of treatment (e.g., identifying users as late and non-late). In this vein, three of our emails, CONTROL, REMINDER and SOCIAL, are general in the sense of not using any information on the behavior of users prior to the treatment, and can therefore easily be adapted to other settings (e.g. driving alerts, voting, donating blood, or referee reports). On top of that, for cases where information on individual behavior is available to the policy maker, it is important to analyze the potential effects on behavior of using such specific information. In our case, LATE and PENALTY use information on user history in order to directly target non-compliant individuals.

2.4 Randomization

In this section we describe the design and procedures of the field experiment. We start by presenting the timing of the email intervention, as well as the randomization of users into the control and different treatments. Then, we evaluate whether the random assignment of users to the control and different treatments was successfully accomplished. Finally, we comment on attrition rates.

As for the setup of the experiment, we sent emails in two different waves. Wave 1 was sent on July 1st, 2009, when we reached about 36,700 users. Wave 2 was sent on September 15th, 2009, when we reached about 38,300 users. Overall, we reached about 50,000 *different* users.[5]

In Wave 1 we considered all the active users between January 1st and May 5th, 2009 and classified them into two categories: late users and non-late users. An active user is a user who borrowed at least one item during the time interval mentioned. A late user is a user who returned an item after the due date at least once during the time interval. A non-late user is a user who did not return any item late during the time interval. There were a total of 21,571 late users and 15,106 non-late users in Wave 1. Late users were randomly assigned to the five different treatments Control, Reminder, Social, Late and Penalty, while non-late users were randomly assigned to Control, Reminder and Social only. The randomization was carried out at the user level and in order to ensure balance across different libraries, we stratified the randomization using the library at which users signed up.

In Wave 2 we considered all the active users between March 1st and July 31st, 2009. Note that in this case we have users who were already active in Wave 1 and new active users, namely those users who were active only between May and July. With regard to the new active users, about 10,500 individuals, we repeated the randomization procedure as in Wave 1. We first classified the new active users into late and non-late users, 5,191 and 5,301 users, respectively. Second, late users were randomly assigned to the five treatments, while the non-late users were randomly assigned to the Control, Reminder and Social treatments only. Also, as in Wave 1, the randomization was carried out at the user level and in order to ensure balance across different libraries, we stratified the randomization using the library codes where users signed up. The active users in Wave 2 who were also active in Wave 1, about 28,500 individuals, received exactly the same email as in Wave 1. Exceptions were those users who were allocated to Late or Penalty in Wave 1 but who, during the interval between March 1st 2009 and

[5] In each wave we sent about 50,000 emails but not all emails were actually delivered. About 30% of email addresses turned out to be invalid and the email messages were returned to the server as messages that were never delivered. We therefore restrict our analysis to those users, to whom the message was delivered.

July 31st 2009, were never late again. There were about 700 of such users, who were excluded from the randomization, and hence received no email in Wave 2. Therefore, there was a total of 20,556 late users and 17,725 non-late users in Wave 2.

Table 2 reports the descriptive statistics of all users, both non-late and late, who were randomly assigned to treatments Control, Reminder and Social in Waves 1 (top) and 2 (bottom). Table 3 reports the descriptive statistics of late users only, randomly assigned to the five treatments in Waves 1 (top) and 2 (bottom). Note that late users in Control, Reminder and Social appear in both Tables 2 and 3. The last column in Tables 2 and 3 report the p-values for the F-Test of equality of variable means across all groups.

[Tables 2 and 3 here]

Consistent with the random assignment of users to treatments, the average user has similar values in the observable characteristics across the different treatments. In fact, as shown by the p-values in the last column in both Tables 2 and 3, the null hypothesis of equality in the means can rarely be rejected. An exception is the proportion of foreigners, possibly due to the valid email address correction (see footnote 5). However, the mean values do not show sizable differences.

As for the characteristics of the average user in the Network of the Public Libraries in the city of Barcelona, 42% of users are male users and the proportion of foreigners is around 30%. The average age is 33. The typical user also borrows quite frequently, with the average total number of loans between January and November exceeding 30. Finally, the majority of borrowed items are books (60%), followed by DVDs (28%) and CDs (9%). Magazines comprise the least frequent type of loans.

From Tables 2 and 3, we can also see the magnitude of the problem of late returns in the Network of Public Libraries in Barcelona. Overall, considering both late and non-late users, 30% of loans per user are returned later than the due date. Moreover, considering only those users who have been late at least once, around 60% of the loans per user are returned after the due date. Furthermore, the typical user returns the borrowed items on average more than a day and a half later than the due date when we consider all late and non-late users. When we only consider late users, the typical user returns the borrowed items on average 6.5 days later than the due date. This shows that returning items late is a common, extended and pervasive habit among the public library users in Barcelona.

In our analysis, as is standard practice in any randomized field experiment, we concentrate on the post-treatment period, that is, on the behavior of users after the email intervention. For those users who received the email message in Wave 1, the post-treatment starts on the 1st of July. For those users who got the email for the first time in Wave 2, the post-treatment starts on the 15th of September. However, not all users who received the email treatment appear in the post-treatment period, that is, some users do not borrow any item at any time in the post-treatment period, so that we cannot observe their compliant or non-compliant behavior. One important issue that needs to be addressed is whether the randomization is still valid when we look at those users whose behavior can actually be observed during the post-treatment period. In particular, we would like to know whether attrition rates between pre and post-treatment periods are significantly different across the control and treatment groups. To address this issue, we define, separately for Waves 1 and 2, the attrition rates, that is, the share of users who received the email treatment but who did not borrow any item in the post-treatment period.

[Table 4]

On average, between 51 and 54% (see column (1) in Table 4), and 46 and 47% (see column (4) in Table 4), of emailed users did not borrow any item in the post-treatment period. However, that is unlikely due to the email intervention, but rather reflects natural fluctuations in borrowing rates over time.[6] More importantly, the null of equal attrition rates among control and treatment groups is not rejected at standard levels of significance, regardless of whether we use individual or joint tests, as shown in columns (2) and (5) of Table 4. When we add library fixed effects (shown in columns (3) and (6)), the coefficients on the treatments are not significant at the 5% level, although they come out jointly significant because library fixed effects are individually significant.[7] To summarize, this analysis prevents possible concerns about attrition being a handicap for the interpretation of our results.

[6]Indeed, computing the comparable attrition rates for those users with unknown email, we get an average of 50%. This shows that the attrition rates we observe after treatment are a rule rather than an exception.

[7]We also redid Tables 2 and 3 for those users who were treated and did borrow items in the

2.5 Identification Strategy

We are interested in evaluating the effect of email messages on the behavior of users. We will focus on two different dependent variables. First, we look at the proportion of late returned items per user (*Proportion Late*). This is a direct measure of how users comply with the rule. Second, we use the average number of days between the return date and the due date per user (*"Actual–Due" Date*). When this difference is positive the item was returned late and when this difference is negative the item was returned early compared to the due date. In contrast to the first dependent variable, which measures late/non-late per item in a binary way, this second variable also takes into account the extent of late or early returns.

In a randomized experiment like ours, the causal effect of the treatments can be estimated as follows:

$$Y_i = \alpha + \beta_1 Reminder_i + \beta_2 Social_i + \beta_3\ Late_i + \beta_4 Penalty_i + \epsilon_i \tag{1}$$

where the dependent variable Y_i is either (i) the proportion of late returns per user, or (ii) the average number of days between the return date and the due date per user.[8] *Reminder*, *Social*, *Late*, and *Penalty* are dummy variables taking a value of 1 when user i was assigned to REMINDER, or SOCIAL, or LATE, or PENALTY, respectively. The omitted treatment to which these variables are compared is CONTROL.

Consistent with our design, we will estimate equation (1) in two different ways. First, we compare REMINDER and SOCIAL to CONTROL for all users, independent of whether they were late or not in the pre-treatment period.[9] Second, we compare REMINDER, SOCIAL, LATE and PENALTY to the CONTROL restricted to all users who were late at least once in the pre-treatment period.

post-treatment period (available upon request). We obtained the same results, qualitatively speaking, showing that the control and treated groups are comparable in all the observable characteristics.

[8]Note that the dependent variables are obtained by collapsing all the transactions at the user level. For example, for a user with 5 transactions that was late with 4 of them has a proportion of late returns of 4/5. In the subsequent analysis, when we add control variables, we also collapse them at the user level.

[9]Here, to be precise, we estimate $Y_i = \alpha + \beta_1 Reminder_i + \beta_2 Social_i + \epsilon_i$ for all users who received a CONTROL, REMINDER, or SOCIAL treatment.

3 Results

3.1 Average Treatment Effects

We estimate equation (1) by OLS. Table 5 reports the results for Control, Reminder, and Social, covering all users, both late and non-late users, who got one of these emails in Waves 1 and 2. Table 6 reports the results for all five treatments restricted to the late users only.

[Tables 5 and 6 here]

The first three columns in both Tables 5 and 6 refer to the proportion of late returns per user, while the last three columns refer to the average number of days between the return date and due date per user. In both cases the first column reports the results of estimating equation (1) without any controls. The second column controls for users' demographics, such as gender, whether the user is foreign or not, and for different age intervals. It also includes controls for different months between July and November, as well as the number of borrowed items. Finally, in the second column we also add controls for users' behavior prior to the treatment, which measures their propensity for late returns and for the average number of days between the return date and the due date per user, prior to the treatment. The third column adds more controls in addition to all the previous variables, accounting for the item type (whether it refers to a book, DVD, CD or a magazine), as well as library fixed effects.[10]

We start by commenting on the results of Table 5. Both Reminder and Social are significant and negative, showing that both email treatments significantly reduce the proportion of late returns and the number of days between the return date and the due date. Furthermore, the more controls we add, the smaller the standard errors become. Taking the estimates of the third column, receiving a Reminder email decreases the proportion of late returns by 1.4 percentage points with respect to Control, while in the case of Social, the reduction is 1.8 percentage points. Evaluated at the mean propensity of being late for the control group (approximately 36 percent), the reduction in late returns lies between 4 percent (Reminder) and 5 percent (Social). Moreover, receiving a treatment email also significantly decreases the number of days between

[10]In all specifications, we discard transactions that were due on a holiday, when the library was closed.

the return date and the due date: the REMINDER and SOCIAL emails decrease this difference on average by almost half a day with respect to CONTROL. Note also that the coefficients of the REMINDER and the SOCIAL emails are not statistically different from each other, meaning that moral suasion did not affect users' behavior differently from the general reminder.

From Table 6, when comparing all four treatments for users who were late at least once in the pre-treatment period, we see that all four of them are significant; both for the proportion of late returns per user and for the average number of days between the return date and the due date per user. For instance, from column (3) we see that the treatment effects (compared to the control) range from -2.4 percentage points for the REMINDER to -4.3 percentage points for the PENALTY. As for the number of days between the return date and the due date, the reduction lies between 0.54 and 0.87 days. Clearly, the most effective treatment seems to be the PENALTY treatment, reducing the proportion of late returns per user by 4.3 percentage points and the average number of days between the return date and the due date per user by almost a day. Evaluated at the means of the control group, this corresponds to a reduction in 10 percent for the proportion of late returns, and a reduction of over 100 percent for the number of days between the return and the due date. Moreover, for the proportion of late returns, the coefficient estimates of the REMINDER and PENALTY treatments are significantly different from each other, showing that the late identification and the penalty reminder make a significant contribution on top of a general reminder.

One may wonder whether the effect mainly comes from the proportion of items that are pending at the time of receiving one of the email treatments or whether it is also the case that rule compliance improves more generally. This is important to understand when we think of the applicability to other settings. In order to address this question, we first create a variable, called *Pending*, which calculates the proportion of pending items per user at the time of receiving an email. Then, we interact the treatment dummies with the proportion of pending items at the user level. Table 7 reports the results.

[Table 7 here]

As can be seen, the interaction terms are insignificant for the proportion of late returns (columns (1) and (3)). Therefore, the effects found in Tables 5 and 6 came not only from the proportion of loans that were pending at the time of the email intervention; instead, the treatments affected all users' behavior, whether items were pending or not. On the other hand, for the average number of days between the return date and the due date (columns (2) and (4)), the interaction terms are negative and significant, implying that users with a larger proportion of pending items return their items earlier than users with a lower proportion of pending items.

To sum up, the results from this section show that a simple email is effective in promoting better compliance with rules. Furthermore, the results are highly robust with regard to other specifications. If instead of collapsing the data at the user level, we estimate random effects with transaction level data, the results we obtain are both qualitatively and quantitatively similar (available upon request). Finally, note again that the intervention mechanism is non-invasive, virtually costless and readily applicable to other settings. In this light, the capability to reduce the proportion of late returns by 10 percent, as it is the case for the PENALTY email, appears to be an attractive option.

3.2 Duration of the Treatment Effect

Having shown that receiving an email has a significant effect on behavior, we now address the question related to the duration of the effect. This is important to fully evaluate the impact of such an intervention. To this end, we partition the post-treatment period into four different time windows: (i) July 1-July 31: the effect in the first month following the first wave of emails, (ii) August 1-September 14: the time interval between a month after the first wave of emails and the beginning of the second wave, (iii) September 15-October 15: the effect one month after the second wave of emails, and (iv) after October 15.

Table 8 reports the estimates for equation (1) separately for the four time windows. The first page of Table 8 refers to treatments CONTROL, REMINDER, and SOCIAL, covering all users, while the second page of Table 8 reports the results for all five treatments (restricted to previously late users only).

[Table 8 here]

The tables show that the effect of getting an email is short term, but it is replicated after getting a second email. No matter whether we use the proportion of late returns per user as a dependent variable, or the average number of days between the return date and the due date, the effect lasts for one month. The first emails that were sent on July 1 had an effect in the period July 1-July 31, but the effect becomes insignificant in the period August 1-September 15. The same pattern can be observed for the emails that were sent on September 15. For most email messages (see the second page of Table 8), we can reject the null that treatments are the same in the first and the second time window. However, the treatment effects are the same for the first and the third time window.[11] Therefore, users who stopped reacting to the first email react again upon reception of the second message, in a comparable manner.

3.3 Heterogenous Treatment Effects by User Characteristics

After estimating the average treatment effect of sending different emails, we now proceed to the analysis of heterogeneous reactions depending on relevant user-specific characteristics. We start by testing for differential treatment effects that depend on users' previous behavior in terms of late returns/days between return and due date. Afterwards, we study whether there are significant differences in behavior depending on age, gender and nationality.

3.3.1 Previous Compliance with the Rule

It is conceivable that the reaction to the different treatments is related to the users' compliance history, that is, their behavior prior to the treatment. To test for this, we interact the treatment variables with *Prior Late* and *Prior "Actual–Due"*. *Prior Late* and *Prior "Actual–Due"* refer to the average user-specific proportion of late returns/days between return and due date in the pre-treatment period.

[Table 9 here]

Table 9 reports the results. We observe that the interaction terms are mostly negative and significant, suggesting that the less rule-compliant users were in the pre-treatment, the stronger is their reaction to the treatments. When we compare the treatments to CONTROL according to the proportion of late returns (columns (1) and

[11] There is one exception, with PENALTY and the proportion of late as the dependent variable. Here, the effect is stronger for the first email than for the second email.

(3)), we see that the REMINDER treatment has a stronger effect on those users who had a higher proportion of late returns prior to the treatment. When the treatment variables are interacted with the user-specific *Prior "Actual–Due"* (columns (2) and (4)), we see that the previous non-compliers have a stronger reaction to the REMINDER message, but also to the LATE and PENALTY messages.

To summarize, the email treatments are especially effective in changing the behavior of a very relevant sample of users, namely those breaking the rule more often. Also, it is important to see that there are no crowding out effects. For users who have a value of *Prior Late* and *Prior "Actual–Due"* equal to 0, the estimated treatment effects are still negative (some of them significant), suggesting a positive effect on the "good types" as well.

3.3.2 Age

We now test for differential treatment effects that are related to different age groups. To this end, we reproduce the estimations of equation (1) separately for the following age groups: below 20 years of age, between 20 and 40, between 40 and 60, and above 60. Table 10 reports the results.

[Table 10 here]

When we compare REMINDER and SOCIAL for all users (first page of Table 10), we see the strongest reaction to the emails coming from users in the age categories 20 to 40 and 40 to 60. For users between 20 and 40, both emails are significant, reducing the proportion of late returns per user by around 2 percentage points and the average number of days between the return date and the due date per user by more than half a day. For users between 40 and 60, the effect of a treatment email is a reduction of the proportion of late returns by up to 2.6 percentage points, and a reduction in the average number of days between the return date and the due date of up to 0.9 days. For the youngest and oldest age groups, no significant effects are observed. Overall, differences across age groups are modest and we cannot reject the null of equal treatment effects.

When we look at late users only (second page of Table 10), the strongest reaction to the email treatments again comes from users in the age classes 20 to 40 and 40 to 60, at least for the proportion of late returns. However, differences are not large enough to reject the null of equality across groups. An interesting feature shown in the table is that the Penalty treatment is significant in all age groups for at least one of the two measures we look at. This shows that the Penalty treatment is effective in all age groups. Finally, when we look at the highest age group, i.e. users above 60, we see that when the effects are significant they become very large, reducing the proportion of late returns per user by even 10 percentage points for Late and 8.7 percentage points for Penalty treatments.

In sum, even though we observe some differences of treatment effects across age groups, these are generally not large enough to reject the null of equality. As for the different messages, it turns out that the Penalty treatment is particularly effective and seems to work independent of the users' age group.

3.3.3 Gender

Whether and why gender matters has increasingly attracted economists' attention. In a recent comprehensive survey, Croson and Gneezy (2009) find that women and men differ along some dimensions (e.g. competitiveness), but not necessarily in others (social preferences revealed in lab experiments). Our data offer a rare opportunity to measure gender differences in rule compliance in daily life, and also the reaction to different email treatments. For the subsequent analysis, we construct interaction variables between our gender variable, $Male$, and the treatment dummy variables.

[Table 11 here]

Table 11 reports the results. As for the $Male$ dummy, it is statistically not significant, meaning that in the control group, women and men show similar patterns in compliant behavior.[12] As for the estimated interaction terms, the coefficients are (with one exception) insignificant, indicating that there are no gender differences in the reaction to the emails. In other words, both women and men are highly comparable when it comes to rule compliance and the reaction to messages aimed at promoting rule compliance.

3.3.4 Nationality

There is sound evidence that nationality is an important determinant of behavior in a variety of settings. Fisman and Miguel (2007), for example, show interesting nationality

[12]We find the same result if we do not include previous compliance as a control.

differences in the determinants of corruption. Our database allows us to distinguish between the users' countries of origin, and hence we can evaluate whether the behavior of users differs by nationality, and whether there are differential reactions to receiving an email based on users' nationality.

We classify users into 8 geographical areas according to their nationality: (i) Spain, (ii) Northern and Central Europe (Germany, Belgium, Denmark, Finland, Netherlands, Norway, Sweden, Switzerland, Austria), (iii) Southern and Western Europe (France, Italy, Greece, Portugal), (iv) English speaking countries (UK, US, Canada, Ireland, and Australia), (v) Eastern Europe and Russia (Bulgaria, Croatia, Slovakia, Estonia, Hungary, Lithuania, Poland, Rumania, Russia, Czech Republic, Ukraine, Georgia, Armenia), (vi) Latin America (Argentina, Bolivia, Brazil, Colombia, Cuba, Dominican Republic, Ecuador, Guatemala, Honduras, Mexico, Nicaragua, Paraguay, Peru, El Salvador, Uruguay, Venezuela, Chile, Costa Rica, Panama), and (vii) Asia (Philippines, Japan, Nepal, China, India, South Korea). Spain accounts for the vast majority of users (around 70%), followed by Latin America with 19%, Southern and Western Europe with 6%, and at the bottom of the distribution is Asia with 1%.

We first analyze whether foreign users differ in their proportion of late returns with respect to Spaniards. Table A.1 in the appendix reports the average user specific propensity for being late in the pre and post-treatment period by nationality groups (columns (1) and (2), respectively), where the omitted variable is Spaniards. It is clear that there are significant differences. The proportion of late returns in nationality groups (iii) to (vi) is higher than that presented by Spaniards. Users from Latin America and from the English speaking countries are among those geographical areas that show the highest differential with respect to Spaniards. On the other hand, Asian users seem to show a lower propensity for being late than Spaniards.

An interesting question is whether there are differential treatment effects that are related to different nationalities. Table 12 reports the results on the proportion of late returns per user and on the average number of days between the return date and the due date per user for the seven nationality groups separately.

[Table 12]

There are remarkable differences. First, users from English speaking countries react significantly to every single treatment. They reduce the proportion of late returns by up to 30 percentage points and reduce the average number of days between the return date and the due date by up to 8.5 days. Previously late users from Asia also react significantly, in particular to the treatments Reminder, Late and Penalty. With the exception of Spain, we do not find consistent and significant effects for the other nationality groups.

We now directly compare the effects found for Spaniards with the effects found for English speaking and Asian countries, controlling for different initial propensities of being late, as well as different reactions depending on prior propensity to be late. Given that different nationality groups show very different proportion of late returns per user, as well as a different average number of days between the return date and the due date per user, one concern might be that some nationalities react more strongly not because of the nationality but because they had a very different compliant behavior to begin with. To deal with such concern and to test for the robustness of the results, we have replicated the analysis in Tables A.2 and A.3, including interactions between prior behavior and the treatment. As can be seen from Table A.2, users coming from English speaking countries react significantly more than Spaniards, for both measures of the dependent variable. For Asian users, as shown in Table A.3, we also see that the effect is significantly higher than for Spaniards, but only for the late users and treatments Reminder and Penalty. As such, users from English speaking countries and Asian users react strongly, despite having very different initial levels of compliance. Finally, we did a similar exercise for the other nationality groups, but we did not find significant results (all results are available upon request).

4 Conclusions

In this paper we study the effect of a very simple, versatile, and virtually costless mechanism, such as sending email messages, on promoting compliance with rules. The study was conducted in the Public Libraries of Barcelona, where compliance with rules means returning items on time. What makes our setting unique is that we observe a large number of users in a daily-life situation, where rules are simple and well-defined, and where compliance is perfectly measurable. The users are diverse in terms of gender, age and nationality, which allows us to study different reactions depending on relevant user characteristics.

Using the methodology of a randomized field experiment, we show that sending email messages helps to promote compliance with rules. The largest effect comes from an email reminding users of the penalties associated with late returns, which decreases the proportion of late returns by 10 percent, and the average number of days between the return date and the due date by over 100 percent. Yet, the effects are substantially bigger for certain subgroups. For instance, users with a high proportion of late returns in the pre-treatment period react more strongly than the other users do. Also, age and nationality appear to affect reactions to the messages. In contrast, and maybe somewhat surprisingly, we find no evidence for gender differences in rule compliance and in the reaction to receiving one of the email messages.

References

[1] Andreoni, James and Vesterlund, Lise (2001), "Which Is the Fair Sex? Gender Differences in Alstruism," *Quarterly Journal of Economics*, 116:293-312.

[2] Andreoni, James and Rao, Justin M. (2010), "The Power of Asking: How Communication Affects Selfishness, Empathy and Altruism," mimeo.

[3] Ayres, Ian, Raseman, Sophie and Shi, Alice (2009), "Evidence From Two Large Field Experiments that Peer Comparison Feedback Can Reduce Energy Usage," NBER W.P. 15386.

[4] Benabou, Roland and Tirole, Jean (2003), "Intrinsic and Extrinsic Motivation," *Review of Economic Studies*, 70:489-520.

[5] Benabou, Roland and Tirole, Jean (2006), "Incentives and Pro-Social Behavior," *American Economic Review*, 96(5):1652-1678.

[6] Charness, Gary and Dufwenberg, Martin (2006). "Promises and Partnership," *Econometrica*, 74(6):1579-1601.

[7] Charness, Gary and Dufwenberg, Martin (2010). "Participation," *American Economic Review*, forthcoming.

[8] Charness, Gary and Gneezy, Uri (2007), "Strong Evidence for Gender Differences in Investment," mimeo.

[9] Charness, Gary and Rustichini, Aldo (2009), "Gender Differences in Cooperation with Group Membership," mimeo.

[10] Fong, Christina and Luttmer, Erzo (2009), "What Determines Giving to Hurricane Katrina Victims? Experimental Evidence on Racial Group Loyalty," *American Economic Journal: Applied Economics*, 1(2):64-87.

[11] Croson, Rachel and Buchan, Nancy (1999), "Gender and Culture: International Experimental Evidence from Trust Games," *American Economic Review P&P*, 89(2):386-391.

[12] Croson, Rachel and Gneezy, Uri (2009), "Gender Differences in Preferences," *Journal of Economic Literature*, 47(2):1-27.

[13] Dal Bó, Ernesto and Dal Bó, Pedro (2009), "Do the Right Thing: The Effect of Moral Suasion on Cooperation," mimeo.

[14] Ellingsen, Tore and Johannesson, Magnus (2004), "Promises, Threats and Fairness," *Economic Journal*, 114(495):397-420.

[15] Ellingsen, Tore and Johannesson, Magnus (2008), "Anticipated Verbal Feedback Induces Altruistic Behavior," *Evolution and Human Behavior*, 29(2):100-105.

[16] Fellner, Gerlinde, Sausgruber, Rupert and Traxler, Christian (2009), "Testing Enforcement Strategies in the Field: Legal Threat, Moral Appeal and Social Information," mimeo.

[17] Fernandez, Raquel (2007a), "Culture and Economics," Forthcoming: *New Palgrave Dictionary of Economics*, 2nd edition, edited by Steven N. Durlauf and Lawrence E. Blume. Palgrave Macmillan.

[18] Fernandez, Raquel (2007b), "Culture and Economics". *Journal of the European Economic Association*, 5(2-3):305-332.

[19] Fisman, Ray and Miguel, Edward (2007), "Corruption, Norms, and Legal Enforcement: Evidence from Diplomatic Parking Tickets," *Journal of Political Economy*, 115(6):1020-1048.

[20] Funk, Patricia (2010), "Social Incentives and Voter Turnout: Evidence from the Swiss Mail Ballot System," *Journal of the European Economic Association*, 8(5): 10771103.

[21] Gächter, Simon, Herrmann, Benedikt and Thöni, Christian (2010), "Culture and Cooperation," mimeo.

[22] Gerber, Alan S., Green, Donald P., and Larimer, Christopher W. (2008), "Social Pressure and Voter Turnout: Evidence from a Large-Scale Field Experiment," *American Political Science Review*, 102(1):33-48.

[23] Gneezy, Uri and Rustichini, Aldo (2000), "A Fine is a Price," *Journal of Legal Studies*, 29(1):1-18.

[24] Guiso, Luigi, Sapienza, Paola and Zingales, Luigi (2009), "Cultural Biases in Economic Exchange," *Quarterly Journal of Economics*, 124(3):1095-1131.

[25] Herrmann, Benedikt, Thöni, Christian and Gächter, Simon (2008), "Antisocial Punishment Across Societies," *Science*, 319:1362-1367.

[26] Karlan, Dean, McConnell, Margaret, Mullainathan, Sendhil and Zinman, Jonathan (2011), "Getting to the Top of Mind: How Reminders Increase Saving," mimeo.

[27] Levitt, Steven D. and List, John A. (2007), "What do Laboratory Experiments Measuring Social Preferences Tell Us about the Real World," *Journal of Economic Perspectives*, 21(2):153-174.

[28] Luttmer, Erzo F.P. and Singhal, Monica (2010), "Culture, Context, and the Taste for Redistribution," *American Economic Journal: Economic Policy*, forthcoming.

[29] Mellstroem, Carl and Johannesson, Magnus (2008), "Crowding Out in Blood Donation: Was Titmuss Right?" *Journal of the European Economic Association*, 6(4):845-863.

[30] Niederle, Muriel and Vesterlund, Lise (2007), "Do Women Shy Away from Competition? Do Men Compete Too Much?" *Quarterly Journal of Economics*, 122:1067-1101.

[31] Schultz, P. Wesley, Nolan, Jessica M., Cialdini, Robert B., Goldstein, Noah J. and Griskevicius, Vladas (2007), "The Constructive, Destructive, and Reconstructive Power of Social Norms," *Psychological Science* 18:429-434.

Table 1—Email Messages

E-mail	Text
Control	Dear User, In the next webpage you will find information on the services and activities offered by the Libraries of Barcelona: http://www.bcn.es/biblioteques/ Best wishes, Libraries of Barcelona
General ***Reminder***	Dear User, **If at some point you borrow an item from the library, please remember that you have to return it on time.** Best wishes, Libraries of Barcelona In the next webpage you will find information on the services and activities offered by the Libraries of Barcelona: http://www.bcn.es/biblioteques/
Social *Motivation*	Dear User, **For a good functioning of the Public Libraries it is important to return the items that are borrowed on time.** If at some point you borrow an item from the library, please remember that you have to return it on time. Best wishes, Libraries of Barcelona In the next webpage you will find information on the services and activities offered by the Libraries of Barcelona: http://www.bcn.es/biblioteques/
Identification ***Late***	Dear User, **In the last months you have returned an item late.** If at some point you borrow an item from the library, please remember that you have to return it on time. Best wishes, Libraries of Barcelona In the next webpage you will find information on the services and activities offered by the Libraries of Barcelona: http://www.bcn.es/biblioteques/
Identification Late and Reminder of the ***Penalty***	Dear User, In the last months you have returned an item late. If at some point you borrow an item from the library, please remember that you have to return it on time. **Remember that the time that a user will be excluded from the possibility of borrowing an item will be the same number of natural days elapsed since the day that the item should have been returned. The maximum period for exclusion is one year.** Best wishes, Libraries of Barcelona In the next webpage you will find information on the services and activities offered by the Libraries of Barcelona: http://www.bcn.es/biblioteques/

Notes: The text in bold refers to the new addition of the treatment email. The words in bold in the first column represent the labels we will use in the paper.

TABLE 2
User Randomization into Treatments CONTROL-REMINDER-SOCIAL

	CONTROL			REMINDER			SOCIAL			***P*-Value**
	Obs.	**Mean**	Std. Dev.	Obs.	**Mean**	Std. Dev.	Obs.	**Mean**	Std. Dev.	Equ. Means
					Wave 1 (Active between 1.January-5.May)					
Male	9438	**0.42**	0.49	9059	**0.42**	0.49	9423	**0.42**	0.49	0.67
Age	9448	**32.71**	13.83	9062	**32.76**	13.89	9434	**33.07**	13.78	0.16
Foreign	9467	**0.28**	0.45	9080	**0.30**	0.46	9452	**0.30**	0.46	0.07
Proportion Late	9467	**0.33**	0.39	9080	**0.33**	0.39	9452	**0.33**	0.39	0.94
"Actual - Due" Date	9376	**1.74**	16.75	8995	**1.53**	16.37	9349	**1.31**	15.86	0.19
Nr. Loans Total	9467	**31.51**	53.46	9080	**31.65**	52.58	9452	**32.73**	58.33	0.25
Nr. Loans 2009 - Half 1	9467	**11.92**	18.80	9080	**11.89**	19.01	9452	**12.48**	22.21	0.08
Book	9467	**0.60**	0.42	9080	**0.60**	0.42	9452	**0.61**	0.42	0.30
CD	9467	**0.09**	0.23	9080	**0.10**	0.23	9452	**0.09**	0.23	0.49
DVD	9467	**0.28**	0.37	9080	**0.28**	0.37	9452	**0.27**	0.36	0.32
Magazine	9467	**0.03**	0.13	9080	**0.02**	0.12	9452	**0.02**	0.11	0.12
					Wave 2 (Active between 1.March-31.July)					
Male	10037	**0.42**	0.49	9758	**0.41**	0.49	10151	**0.41**	0.49	0.81
Age	10049	**32.74**	14.09	9763	**32.49**	13.98	10157	**32.79**	13.73	0.28
Foreign	10064	**0.28**	0.45	9782	**0.29**	0.45	10180	**0.30**	0.46	0.01
Proportion Late	10063	**0.35**	0.39	9782	**0.36**	0.39	10180	**0.35**	0.39	0.92
"Actual - Due" Date	9923	**1.58**	14.69	9639	**1.54**	14.82	10047	**1.48**	14.33	0.89
Nr. Loans Total	10064	**30.28**	52.25	9782	**30.12**	51.25	10180	**31.40**	56.98	0.18
Nr. Loans 2009 - Half 1	10064	**11.18**	18.56	9782	**11.01**	18.67	10180	**11.67**	21.83	0.05
Book	10064	**0.62**	0.41	9782	**0.62**	0.41	10180	**0.61**	0.41	0.49
CD	10064	**0.09**	0.22	9782	**0.09**	0.22	10180	**0.09**	0.22	0.47
DVD	10064	**0.27**	0.36	9782	**0.27**	0.36	10180	**0.27**	0.36	0.31
Magazine	10064	**0.03**	0.13	9782	**0.03**	0.13	10180	**0.03**	0.12	0.23

Notes: All variables refer to all users, late and non-late, who were active in windows 1 (1 January-15 May) and 2 (1 March-31 July). All variables are obtained at the user level. Male takes a value of 1 in case of male, Age shows the user's age in years, and Foreign is a dummy variable taking a value of 1 in the case of Non-Spanish. Proportion Late measures the proportion of late returns per user, and "Actual - Due" Date measures the average number of days between the return date and the deadline per user. Number of Loans represents the number of loans per user. Book, CD, DVD and Magazine reflects the user's average share of Books, CD's, DVD's and Magazines. The *P*-Value in the last column is for the F-Test of equality of variable means across all three groups.

TABLE 3
User Randomization into Treatments CRONTOL-REMINDER-SOCIAL-LATE-PENALTY

	CONTROL			**REMINDER**			**SOCIAL**			**LATE**			**PENALTY**			***P*-Value**
	Obs.	**Mean**	Std. Dev.	Obs.	**Mean**	Std. Dev.	Obs.	**Mean**	Std. Dev.	Obs.	**Mean**	Std. Dev.	Obs.	**Mean**	Std. Dev.	Equ. Means
Wave 1 (Active between 1.January-5.May)																
Male	4315	**0.43**	0.49	4182	**0.43**	0.50	4351	**0.43**	0.50	4333	**0.43**	0.50	4304	**0.42**	0.49	0.97
Age	4321	**32.20**	12.78	4187	**32.30**	12.83	4355	**32.48**	12.55	4343	**32.41**	12.76	4312	**32.23**	12.58	0.82
Foreign	4331	**0.33**	0.47	4195	**0.35**	0.48	4367	**0.35**	0.48	4355	**0.34**	0.48	4323	**0.35**	0.48	0.08
Proportion Late	4331	**0.59**	0.33	4195	**0.58**	0.33	4367	**0.59**	0.33	4355	**0.58**	0.33	4323	**0.59**	0.33	0.22
"Actual - Due" Date	4270	**6.61**	20.79	4143	**5.94**	20.42	4301	**5.68**	19.37	4288	**5.91**	19.08	4269	**5.75**	18.22	0.20
Nr. Loans Total	4331	**46.15**	67.88	4195	**47.52**	67.61	4367	**48.54**	76.08	4355	**47.34**	74.48	4323	**48.00**	74.16	0.62
Nr. Loans 2009 - Half 1	4331	**17.48**	24.19	4195	**17.91**	24.63	4367	**18.50**	29.57	4355	**17.88**	25.38	4323	**18.35**	27.10	0.39
Book	4331	**0.50**	0.39	4195	**0.49**	0.39	4367	**0.50**	0.39	4355	**0.49**	0.39	4323	**0.48**	0.39	0.20
CD	4331	**0.12**	0.24	4195	**0.12**	0.24	4367	**0.12**	0.24	4355	**0.13**	0.24	4323	**0.12**	0.24	0.77
DVD	4331	**0.35**	0.36	4195	**0.36**	0.37	4367	**0.35**	0.36	4355	**0.36**	0.36	4323	**0.36**	0.36	0.48
Magazine	4331	**0.03**	0.12	4195	**0.03**	0.13	4367	**0.03**	0.12	4355	**0.03**	0.12	4323	**0.03**	0.12	0.69
Wave 2 (Active between 1.March-31.July)																
Male	4069	**0.43**	0.49	4014	**0.43**	0.49	4178	**0.42**	0.49	4158	**0.42**	0.49	4060	**0.42**	0.49	0.94
Age	4078	**32.18**	12.85	4019	**31.82**	12.74	4180	**32.12**	12.43	4166	**32.31**	12.81	4066	**31.78**	12.46	0.25
Foreign	4086	**0.33**	0.47	4029	**0.34**	0.47	4186	**0.36**	0.48	4178	**0.35**	0.48	4077	**0.37**	0.48	0.01
Proportion Late	4086	**0.62**	0.32	4029	**0.62**	0.32	4186	**0.61**	0.33	4178	**0.61**	0.32	4077	**0.61**	0.33	0.17
"Actual - Due" Date	3989	**6.55**	17.96	3940	**6.50**	18.20	4108	**6.02**	16.93	4067	**6.27**	17.70	3996	**6.23**	16.97	0.65
Nr. Loans Total	4086	**46.52**	68.75	4029	**46.92**	68.29	4186	**48.43**	76.93	4178	**46.78**	74.60	4077	**47.71**	74.96	0.75
Nr. Loans 2009 - Half 1	4086	**17.51**	24.55	4029	**17.67**	25.10	4186	**18.54**	30.35	4178	**17.77**	26.05	4077	**18.38**	27.46	0.32
Books	4086	**0.50**	0.39	4029	**0.49**	0.39	4186	**0.49**	0.39	4178	**0.49**	0.39	4077	**0.48**	0.39	0.63
CDs	4086	**0.12**	0.24	4029	**0.11**	0.23	4186	**0.12**	0.24	4178	**0.12**	0.24	4077	**0.12**	0.24	0.36
DVDs	4086	**0.35**	0.36	4029	**0.36**	0.37	4186	**0.36**	0.36	4178	**0.36**	0.36	4077	**0.36**	0.36	0.74
Magazines	4086	**0.03**	0.13	4029	**0.04**	0.14	4186	**0.03**	0.12	4178	**0.03**	0.12	4077	**0.03**	0.13	0.06

Notes: All variables refer to the late users who were active in windows 1 (1 January-15 May) and 2 (1 March-31 July). All variables are obtained at the user level. Male takes a value of 1 in case of male, age shows the user's age in years, and Foreign is a dummy variable taking a value of 1 in the case of Non-Spanish. Proportion Late measures the proportion of late returns per user, and "Actual - Due" Date measures the average number of days between the return date and the deadline per user. Number of Loans represents the number of loans per user. Book, CD, DVD and Magazine reflects the user's average share of Books, CD's, DVD's and Magazines. The *P*-Value in the last column is for the F-Test of equality of variable means across all five groups.

TABLE 4
Attrition

	Wave 1 (Active between 1.January-5.May)					
	Control-Reminder-Social			Control-Rem.-Social-Late-Penalty		
	(1)	(2)	(3)	(4)	(5)	(6)
Reminder		-0.0115	-0.0133*		-0.0101	-0.0117
		(0.00732)	(0.00731)		(0.0108)	(0.0108)
Social		-0.00189	-0.00272		0.00794	0.00716
		(0.00725)	(0.00723)		(0.0107)	(0.0107)
Late					-0.0155	-0.0168
					(0.0107)	(0.0107)
Penalty					-0.0109	-0.0114
					(0.0107)	(0.0107)
Constant	0.539***	0.544***	0.687***	0.475***	0.481***	0.646***
	(0.00297)	(0.00512)	(0.0185)	(0.00340)	(0.00759)	(0.0214)
Library FE	No	No	Yes	No	No	Yes
Observations	27999	27999	27999	21571	21571	21571
R-squared	0.0000	0.0000	0.006	0.0000	0.0000	0.007
Ho : all coefficients=0 (*p* -values)		0.2446	0.0000		0.1776	0.0000
	Wave 2 (Active between 1.March-31.July)					
	Control-Reminder-Social			Control-Rem.-Social-Late-Penalty		
	(1)	(2)	(3)	(4)	(5)	(6)
Reminder		-0.00349	-0.00536		0.00275	0.00188
		(0.00709)	(0.00708)		(0.0111)	(0.0110)
Social		0.00879	0.00820		0.0208*	0.0213*
		(0.00702)	(0.00701)		(0.0110)	(0.0109)
Late					-0.00314	-0.00215
					(0.0110)	(0.0109)
Penalty					-0.00120	-0.00126
					(0.0110)	(0.0110)
Constant	0.515***	0.514***	0.744***	0.461***	0.458***	0.669***
	(0.00288)	(0.00498)	(0.0246)	(0.00347)	(0.00780)	(0.0288)
Library FE	No	No	Yes	No	No	Yes
Observations	30032	30032	30032	20556	20556	20556
R-squared	0.000	0.000	0.007	0.000	0.000	0.008
Ho : all coefficients=0 (*p* -values)		0.2001	0.0000		0.1736	0.0000

Notes : The dependent variable is a dummy that takes value 1 if the user did not borrow any item in the post-treatment period and 0 otherwise. The top panel refers to Wave 1 and the bottom pannel refers to Wave 2. Columns (1), (2) and (3) refer to all users, while columns (4), (5) and (6) refer to late users only. Standard errors in paranthesis. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE 5

CONTROL-REMINDER-SOCIAL

	Proportion Late			"Actual - Due" Date		
	(1)	(2)	(3)	(4)	(5)	(6)
Reminder	**-0.0129***	**-0.0123***	**-0.0138***	**-0.387***	**-0.395****	**-0.468****
	(0.00777)	**(0.00719)**	**(0.00715)**	**(0.203)**	**(0.192)**	**(0.189)**
Social	**-0.0167****	**-0.0160****	**-0.0184*****	**-0.314**	**-0.296**	**-0.409****
	(0.00772)	**(0.00714)**	**(0.00710)**	**(0.202)**	**(0.190)**	**(0.188)**
CD			0.0850***			3.434***
			(0.0142)			(0.373)
DVD			0.0924***			3.455***
			(0.00862)			(0.229)
Magazine			0.0776***			3.734***
			(0.0225)			(0.600)
August		0.0461***	0.0681***		-0.397	0.525
		(0.0131)	(0.0134)		(0.344)	(0.348)
September		0.00603	0.00730		-2.582***	-2.514***
		(0.0106)	(0.0106)		(0.278)	(0.276)
October		0.0303***	0.0253***		-3.247***	-3.414***
		(0.00924)	(0.00920)		(0.248)	(0.245)
November		-0.391***	-0.375***		-12.74***	-11.91***
		(0.0205)	(0.0204)		(0.545)	(0.540)
Age 20-40		0.00709	-0.00423		0.372	0.00343
		(0.00894)	(0.00897)		(0.240)	(0.238)
Age 40-60		-0.0549***	-0.0610***		-0.976***	-1.172***
		(0.00996)	(0.00996)		(0.266)	(0.263)
Age over 60		-0.105***	-0.104***		-1.748***	-1.620***
		(0.0159)	(0.0159)		(0.420)	(0.416)
Male		0.00540	-0.00146		0.0573	-0.225
		(0.00596)	(0.00597)		(0.159)	(0.157)
Foreign		0.0454***	0.0328***		1.141***	0.683***
		(0.00676)	(0.00684)		(0.180)	(0.181)
Number of Loans		-0.00256***	-0.00321***		-0.0443***	-0.0698***
		(0.000199)	(0.000209)		(0.00524)	(0.00546)
Prior Late		0.331***	0.317***			
		(0.00883)	(0.00884)			
Prior "Actual - Due"					0.227***	0.201***
					(0.00956)	(0.00950)
Constant	0.358***	0.276***	0.379***	-0.583***	1.963***	4.803
	(0.00546)	(0.0114)	(0.146)	(0.143)	(0.294)	(4.105)
Library FE	NO	NO	YES	NO	NO	YES
R-squared	0.000	0.152	0.166	0.000	0.107	0.138
Number of users	14605	14442	14442	14157	13990	13990
H0: Reminder=Social (*p*-value)	0.6245	0.6078	0.5208	0.7204	0.6074	0.7566
H0: Reminder=Social=0 (*p*-value)	0.0769	0.0636	0.027	0.128	0.0995	0.0257

Notes: *Proportion Late* measures the proportion of late returns per user, columns (1)-(2)-(3), and *"Actual - Due" Date* measures the average number of days between the return date and the due date per user, columns (4)-(5)-(6). See different email messages in Table 1. *CD*, *DVD* and *Magazine* are dummy variables for the item type (omitted category: *Book*), *August*, *September*, *October*, *November* months dummies (omitted category: *July*), and *Age 20-40*, *Age 40-60* and *Age over 60* are age dummies (omitted category: *Age under 20*). *Male* takes a value of 1 in case of male, *Foreign* a value of 1 in case of non-Spanish, and *Number of Loans* is the average number of loans per user. *Prior Late* and *Prior "Actual - Due"* refer to proportion of late returns per user and the average number of days between the return date and the due date, both prior to the treatment. Robust standard errors in paranthesis. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE 6
CONTROL-REMINDER-SOCIAL-LATE-PENALTY

	Proportion Late			"Actual - Due" Date		
	(1)	(2)	(3)	(4)	(5)	(6)
Reminder	**-0.0266****	**-0.0235****	**-0.0239****	**-0.535***	**-0.565****	**-0.614****
	(0.0109)	**(0.0102)**	**(0.0101)**	**(0.297)**	**(0.281)**	**(0.276)**
Social	**-0.0275****	**-0.0270*****	**-0.0297*****	**-0.402**	**-0.425**	**-0.549****
	(0.0109)	**(0.0101)**	**(0.0100)**	**(0.295)**	**(0.279)**	**(0.275)**
Late	**-0.0252****	**-0.0274*****	**-0.0271*****	**-0.423**	**-0.496***	**-0.549****
	(0.0108)	**(0.0100)**	**(0.00994)**	**(0.293)**	**(0.278)**	**(0.273)**
Penalty	**-0.0391*****	**-0.0409*****	**-0.0433*****	**-0.674****	**-0.781*****	**-0.879*****
	(0.0108)	**(0.0101)**	**(0.00997)**	**(0.294)**	**(0.279)**	**(0.274)**
CD			0.0863***			3.100***
			(0.0149)			(0.405)
DVD			0.109***			3.173***
			(0.00930)			(0.257)
Magazine			0.109***			3.175***
			(0.0236)			(0.654)
August		0.0261*	0.0508***		-0.528	0.542
		(0.0145)	(0.0148)		(0.393)	(0.399)
September		0.0251**	0.0212*		-2.576***	-2.629***
		(0.0120)	(0.0120)		(0.326)	(0.323)
October		0.0392***	0.0316***		-3.874***	-4.124***
		(0.0104)	(0.0104)		(0.291)	(0.287)
November		-0.518***	-0.502***		-15.40***	-14.69***
		(0.0244)	(0.0242)		(0.683)	(0.675)
Age 20-40		0.0138	-0.00112		0.944***	0.515*
		(0.0103)	(0.0103)		(0.288)	(0.286)
Age 40-60		-0.0461***	-0.0549***		-0.512	-0.786**
		(0.0117)	(0.0117)		(0.325)	(0.321)
Age over 60		-0.0832***	-0.0843***		-0.754	-0.727
		(0.0198)	(0.0197)		(0.543)	(0.536)
Male		0.00577	-0.00151		0.106	-0.139
		(0.00647)	(0.00646)		(0.179)	(0.177)
Foreign		0.0496***	0.0377***		1.078***	0.719***
		(0.00700)	(0.00706)		(0.194)	(0.194)
Number of Loans		-0.00240***	-0.00298***		-0.0539***	-0.0727***
		(0.000191)	(0.000200)		(0.00511)	(0.00533)
Prior Late		0.301***	0.293***			
		(0.0109)	(0.0108)			
Prior "Actual - Due"					0.170***	0.156***
					(0.00969)	(0.00957)
Constant	0.440***	0.301***	0.158	0.759***	2.689***	4.478
	(0.00769)	(0.0145)	(0.150)	(0.209)	(0.369)	(3.690)
Library FE	NO	NO	YES	NO	NO	YES
R-squared	0.001	0.141	0.161	0.000	0.101	0.135
Number of users	12286	12205	12205	11846	11750	11750
H0: Reminder=Social (*p*-value)	0.9309	0.7307	0.5648	0.6554	0.6167	0.8135
H0: Reminder=Late (*p*-value)	0.8995	0.7013	0.7455	0.7043	0.8034	0.8125
H0: General=Penalty (*p*-value)	0.2491	0.0851	0.0532	0.6353	0.4404	0.3365
H0: Late=Penalty (*p*-value)	0.1948	0.1744	0.1027	0.388	0.3019	0.2253
H0: Reminder=Social=Late=Penalty (*p*-value)	0.5471	0.3204	0.2225	0.779	0.605	0.5753
H0: Reminder=Social=Late=Penalty=0 (*p*-value)	0.0072	0.0016	0.0006	0.2129	0.0772	0.0283

Notes: *Proportion Late* measures the proportion of late returns per user, columns (1)-(2)-(3), *and "Actual - Due" Date* measures the average number of days between the return date and the due date per user, columns (4)-(5)-(6). See different email messages in Table 1. CD, DVD and Magazine are dummy variables for the item type (omitted category: Book), August, September, October, November months dummies (omitted category: July), and Age 20-40, Age 40-60 and Age over 60 are age dummies (omitted category: Age under 20). Male takes a value of 1 in case of male, Foreign a value of 1 in case of non-Spanish, and Number of Loans is the average number of loans per user. Prior Late and Prior "Actual - Due" refer to proportion of late returns per user and the average number of days between the return date and the due date, both prior to the treatment. Robust standard errors in paranthesis. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE 7
Differential Treatment Effect with respect to the Proportion of Pending Items

	Control-Reminder-Social		Control-Rem.-Social-Late-Penalty	
	Prop. Late	"Actual - Due" Date	Prop. Late	"Actual - Due" Date
	(1)	(2)	(3)	(4)
Reminder	**-0.00890**	**0.00583**	**-0.0182**	**-0.0522**
	(0.00924)	**(0.238)**	**(0.0131)**	**(0.353)**
Social	**-0.0111**	**0.229**	**-0.0307****	**0.139**
	(0.00915)	**(0.236)**	**(0.0131)**	**(0.350)**
Late			**-0.0231***	**0.111**
			(0.0129)	**(0.346)**
Penalty			**-0.0334****	**-0.349**
			(0.0130)	**(0.350)**
Pending	0.249***	8.985***	0.267***	10.16***
	(0.0142)	(0.369)	(0.0202)	(0.548)
Reminder*Pending	**-0.00897**	**-1.288*****	**-0.0151**	**-1.718****
	(0.0190)	**(0.494)**	**(0.0278)**	**(0.752)**
Social*Pending	**-0.0161**	**-1.826*****	**0.000548**	**-2.334*****
	(0.0190)	**(0.494)**	**(0.0276)**	**(0.748)**
Late*Pending			**-0.00523**	**-1.891****
			(0.0273)	**(0.741)**
Penalty*Pending			**-0.0350**	**-1.844****
			(0.0273)	**(0.741)**
Constant	0.200	-1.347	-0.0436	-3.085
	(0.143)	(3.952)	(0.147)	(3.558)
Controls	YES	YES	YES	YES
Library FE	YES	YES	YES	YES
R-squared	0.204	0.203	0.201	0.200
Number of users	14442	13990	12205	11750
H0: Reminder=Social (*p*-value)	0.8101	0.3443	0.3403	0.5863
H0: Reminder=Late (*p*-value)			0.7086	0.637
H0: Reminder=Penalty (*p*-value)			0.2468	0.3982
H0: Late=Penalty (*p*-value)			0.421	0.1812
H0: Reminder=Social=Late=Penalty (*p*-value)			0.6355	0.4762
H0: Reminder=Social=Late=Penalty=0 (*p*-value)			0.0835	0.6426
H0: Reminder=Social=0 (*p*-value)	0.4404	0.5407		
H0: Reminder*Pend=Social*Pend (*p*-value)	0.7114	0.2792	0.5744	0.4127
H0: Reminder*Pend=Late*Pend (*p*-value)			0.7206	0.8162
H0: Reminder*Pend=Penalty*Pend (*p*-value)			0.4699	0.8655
H0: Late*Pend=Penalty*Pend (*p*-value)			0.2712	0.9491
H0: Reminder*Pend=Social*Pend=Late*Pend=Penalty*Pend (*p*-value)			0.5774	0.8568
H0: Reminder*Pend=Social*Pend=Late*Pend=Penalty*Pend=0 (*p*-value)			0.6655	0.0202
H0: Reminder*Pend=Social*Pend=0 (*p*-value)	0.6977	0.0007		

Notes: This table reports differential treatment effects with respect to the proportion of pending items per user. *Pending* measures the proportion of pending items per user on the moment the email treatment is received, while the interaction terms measure the differential treatment effects of the proportion of pending items. The full set of controls is used, as well as the library fixed effects. See the notes from previous tables. Robust standard errors in paranthesis. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE 8

Treatment Effects over Time (Treatments Control-Reminder-Social)

	Proportion Late				**"Actual - Due" Date**			
	July 1 - July 31	**August 1 - Sept. 14**	**Sept. 15-Oct. 15**	**Oct. 15 onwards**	**July 1 - July 31**	**August 1 - Sept. 14**	**Sept. 15-Oct. 15**	**Oct. 15 onwards**
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Reminder	**-0.0290*** **	**-0.00818**	**-0.0108**	**-0.0149**	**-0.805** **	**-0.0564**	**-0.359** **	**-0.206**
	(0.0112)	**(0.0129)**	**(0.0110)**	**(0.0120)**	**(0.345)**	**(0.341)**	**(0.182)**	**(0.183)**
Social	**-0.0236** **	**-0.00554**	**-0.0235** **	**-0.00739**	**-0.883** **	**0.211**	**-0.545*** **	**-0.251**
	(0.0111)	**(0.0128)**	**(0.0108)**	**(0.0119)**	**(0.350)**	**(0.325)**	**(0.179)**	**(0.192)**
Constant	0.264	0.776***	0.837***	-0.290***	17.78**	8.006***	-7.453	-10.35***
	(0.165)	(0.0665)	(0.175)	(0.0297)	(8.829)	(2.308)	(8.922)	(0.777)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Library FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.132	0.129	0.146	0.109	0.128	0.151	0.184	0.153
Number of users	7029	5569	7379	6340	6934	5485	7200	5797
H0: Reminder=Social (*p*-value)	0.6268	0.8363	0.2465	0.5289	0.8181	0.4101	0.3062	0.8207
H0: Reminder=Social=0 (*p*-value)	0.0225	0.8108	0.0923	0.4626	0.0204	0.6785	0.0087	0.3591
Cross-Equation Joint Tests (*p*-values)	Proportion Late	"Actual-Due" Date						
H0: Reminder: (1)=(2)=(3)=(4)	0.0487	0.0164						
H0: Reminder(1)=Reminder(2)	0.2212	0.0564						
H0: Reminder(3)=Reminder(4)	0.8039	0.6914						
H0: Reminder(1)=Reminder(3)	0.2500	0.2203						
H0: Social: (1)=(2)=(3)=(4)	0.0470	0.0015						
H0: Social(1)=Social(2)	0.2845	0.0049						
H0: Social(3)=Social(4)	0.3159	0.4382						
H0: Social(1)=Social(3)	0.9963	0.3494						

TABLE 8 (continued)

Treatment Effects over Time (Control-Reminder-Social-Late-Penalty)

	Proportion Late				"Actual - Due" Date			
	July 1 - July 31	August 1 - Sept. 14	Sept. 15-Oct. 15	Oct. 15 onwards	July 1 - July 31	August 1 - Sept. 14	Sept. 15-Oct. 15	Oct. 15 onwards
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Reminder	**-0.0617*** **	**-0.0117**	**-0.0296***	**-0.0135**	**-1.325*** **	**-0.0755**	**-0.575** **	**-0.411**
	(0.0154)	**(0.0171)**	**(0.0154)**	**(0.0170)**	**(0.481)**	**(0.483)**	**(0.259)**	**(0.258)**
Social	**-0.0454*** **	**0.000166**	**-0.0224**	**-0.0235**	**-1.318*** **	**0.170**	**-0.613** **	**-0.407**
	(0.0155)	**(0.0171)**	**(0.0152)**	**(0.0167)**	**(0.503)**	**(0.451)**	**(0.252)**	**(0.283)**
Late	**-0.0389** **	**-0.0208**	**-0.0378** **	**-0.0128**	**-0.613**	**-0.513**	**-0.813*** **	**-0.355**
	(0.0154)	**(0.0172)**	**(0.0155)**	**(0.0172)**	**(0.496)**	**(0.461)**	**(0.251)**	**(0.263)**
Penalty	**-0.0754*** **	**-0.0115**	**-0.0288***	**-0.0336***	**-1.415*** **	**-0.383**	**-0.797*** **	**0.0792**
	(0.0153)	**(0.0170)**	**(0.0157)**	**(0.0173)**	**(0.487)**	**(0.436)**	**(0.253)**	**(0.247)**
Constant	0.372**	0.428*	0.0785	-0.300***	21.77**	6.729	-8.830***	-10.82***
	(0.147)	(0.235)	(0.208)	(0.0328)	(10.33)	(6.044)	(2.417)	(0.370)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Library FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.123	0.126	0.129	0.109	0.133	0.157	0.167	0.154
Number of users	6466	5294	6385	5457	6372	5205	6202	4907
H0: Reminder=Social (*p* -value)	0.2832	0.4876	0.6393	0.5527	0.9884	0.5920	0.8814	0.9879
H0: Reminder=Late (*p* -value)	0.1311	0.5939	0.5976	0.9684	0.1248	0.3407	0.3482	0.8395
H0: Reminder=Penalty (*p* -value)	0.3637	0.9939	0.9613	0.2469	0.8444	0.4886	0.3870	0.0560*
H0: Late=Penalty (*p* -value)	0.0153	0.5852	0.5700	0.2368	0.0897*	0.7553	0.9469	0.143
H0: Reminder=Social=Late=Penalty (*p* -value)	0.0673	0.6770	0.7980	0.5953	0.2980	0.3739	0.6985	0.1618
H0: Reminder=Social=Late=Penalty=0 (*p* -value)	0.0000	0.7052	0.1398	0.3676	0.0141**	0.4881	0.0088***	0.1567
Cross-Equation Joint Tests (*p* -values)	Proportion Late	"Actual - Due" Date						
H0: Reminder: (1)=(2)=(3)=(4)	0.0947	0.1151						
H0: Reminder(1)=Reminder(2)	0.0301	0.0209						
H0: Reminder(3)=Reminder(4)	0.4805	0.7655						
H0: Reminder(1)=Reminder(3)	0.1403	0.1431						
H0: Social: (1)=(2)=(3)=(4)	0.2702	0.0493						
H0: Social(1)=Social(2)	0.0482	0.0059						
H0: Social(3)=Social(4)	0.9615	0.7045						
H0: Social(1)=Social(3)	0.2911	0.1678						
H0: Late(1)=Late(2)=Late(3)=Late(4)	0.5951	0.8655						
H0: Late(1)=Late(2)	0.4321	0.8527						
H0: Late(3)=Late(4)	0.2743	0.4075						
H0: Late(1)=Late(3)	0.9626	0.6979						
H0: Penalty: (1)=(2)=(3)=(4)	0.0330	0.0428						
H0: Penalty(1)=Penalty(2)	0.0054	0.0552						
H0: Penalty(3)=Penalty(4)	0.8340	0.1153						
H0: Penalty(1)=Penalty(3)	0.0337	0.2305						

Notes: The table reports treatment effects for different time periods: The first month after the first email was sent (July1-July31), the second 6 weeks after the first email was sent (August 1-September 14), the first month after the second email was sent (September 15-October 15), the effect of the second email after one month (October 15 onwards). The first page of the table encompasses the users in treatments Control-Reminder-Social, as in Table 5, and the second page of the table corresponds to the users in treatments Control-Reminder-Social-Late-Penalty, as in Table 6. The full set of controls is used, as well as the library fixed effects. See the notes from previous tables. Robust standard errors in paranthesis. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE 9
Differential Treatment Effect with respect to Prior Compliance

	Control-Reminder-Social		Control-Reminder-Social-Late-Penalty	
	Prop. Late (1)	"Actual - Due" Date (2)	Prop. Late (3)	"Actual - Due" Date (4)
Reminder	**-0.00243**	**-0.516*** **	**0.00488**	**-0.381**
	(0.00981)	**(0.189)**	**(0.0193)**	**(0.282)**
Social	**-0.0137**	**-0.401** **	**-0.0260**	**-0.450**
	(0.00973)	**(0.188)**	**(0.0193)**	**(0.281)**
Late			**-0.0321***	**-0.414**
			(0.0191)	**(0.279)**
Penalty			**-0.0347***	**-0.705** **
			(0.0191)	**(0.281)**
Prior Late	**0.334*** **		**0.307*** **	
	(0.0149)		**(0.0234)**	
Reminder*Prior Late	**-0.0358***		**-0.0581***	
	(0.0212)		**(0.0331)**	
Social*Prior Late	**-0.0146**		**-0.00728**	
	(0.0210)		**(0.0328)**	
Late*Prior Late			**0.0100**	
			(0.0325)	
Penalty*Prior Late			**-0.0170**	
			(0.0323)	
Prior "Actual - Due"		**0.231*** **		**0.230*** **
		(0.0167)		**(0.0231)**
Reminder*Prior "Actual - Due"		**-0.0826*** **		**-0.124*** **
		(0.0223)		**(0.0296)**
Social*Prior "Actual - Due"		**0.00652**		**-0.0519**
		(0.0237)		**(0.0320)**
Late*Prior "Actual - Due"				**-0.0715** **
				(0.0302)
Penalty*Prior "Actual - Due"				**-0.0910*** **
				(0.0319)
Constant	0.375**	4.878	0.157	4.410
	(0.146)	(4.102)	(0.151)	(3.688)
Controls	YES	YES	YES	YES
Library FE	YES	YES	YES	YES
R-squared	0.166	0.139	0.162	0.136
Number of users	14442	13990	12205	11750
H0: Reminder=Social (*p*-value)	0.2511	0.5425	0.11	0.8073
H0: Reminder=Late (*p*-value)			0.0533	0.9048
H0: Reminder=Penalty (*p*-value)			0.386	0.2485
H0: Late=Penalty (*p*-value)			0.8328	0.2953
H0: Reminder=Social=Late=Penalty (*p*-value)			0.144	0.6429
H0: Reminder=Social=Late=Penalty=0 (*p*-value)			0.1102	0.1673
H0: Reminder=Social=0 (*p*-value)	0.325	0.0163		
H0: Reminder*Comp=Social*Comp (*p*-value)	0.3199	0.0001	0.1253	0.013
H0: Reminder*Comp=Late*Comp(*p*-value)			0.0384	0.0513
H0: Reminder*Comp=Penalty*Comp(*p*-value)			0.2092	0.2506
H0: Late*Comp=Penalty*Comp (*p*-value)			0.3987	0.5104
H0: Reminder*Comp=Social*Comp=Late*Comp=Penalty*Comp (*p*-value)			0.2049	0.069
H0: Reminder*Comp=Social*Comp=Late*Comp=Penalty*Comp=0 (*p*-value)			0.2832	0.0007

Notes: This table reports differential treatment effects with respect to prior compliance. Prior Late measures the user-specific proportion of items that were returned late in the pre treatment period. Prior "Actual - Due" measures the average number of days between the return date and the due date per user in the pre treatment period. The full set of controls is used, as well as the library fixed effects. See the notes from previous tables. Robust standard errors in paranthesis. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE 10
Treatment Effects by Age Groups

	Age below 20		Age 20-40		Age 40-60		Age over 60	
	Prop. Late	"Actual - Due" Date	Prop. Late	"Actual - Due" Date	Prop. Late	"Actual - Due" Date	Prop. Late	"Actual - Due" Date
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reminder	**0.0103**	**-0.0647**	**-0.0221****	**-0.617****	**-0.0160**	**-0.554***	**0.00960**	**0.544**
	(0.0207)	**(0.634)**	**(0.00965)**	**(0.261)**	**(0.0136)**	**(0.291)**	**(0.0283)**	**(0.658)**
Social	**-0.0183**	**-0.458**	**-0.0192****	**-0.358**	**-0.0257***	**-0.896*****	**0.0136**	**1.199***
	(0.0210)	**(0.644)**	**(0.00951)**	**(0.257)**	**(0.0136)**	**(0.292)**	**(0.0282)**	**(0.655)**
Constant	0.491*	-0.299	0.374	11.87*	0.268	-1.455	0.297	-1.039
	(0.268)	(11.25)	(0.269)	(6.202)	(0.234)	(5.520)	(0.794)	(6.801)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Library FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.144	0.115	0.158	0.131	0.158	0.187	0.231	0.276
Number of user	1969	1877	8325	8039	3486	3418	662	656
H0: Reminder=Social (*p* -value)	0.1729	0.5384	0.7689	0.3156	0.4786	0.2457	0.8846	0.3111
H0: Reminder=Social=0 (*p* -value)	0.3874	0.7439	0.044	0.0595	0.1626	0.0083	0.8847	0.1859
Cross-Equation Joint Tests (*p* -values)	Prop. Late	"Actual - Due" Date						
H0: Reminder equal across age groups	0.4276	0.5174						
H0: Social equal across age groups	0.7763	0.1821						

TABLE 10 (continued)
Treatment Effects by Age Groups

	Age under 20		Age 20-40		Age 40-60		Age over 60	
	Prop. Late	"Actual - Due" Date	Prop. Late	"Actual - Due" Date	Prop. Late	"Actual - Due" Date	Prop. Late	"Actual - Due" Date
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Reminder	**0.00779**	**-0.796**	**-0.0343*** **	**-0.558**	**-0.0106**	**-0.641**	**-0.0486**	**-0.275**
	(0.0316)	**(0.997)**	**(0.0128)**	**(0.359)**	**(0.0204)**	**(0.458)**	**(0.0525)**	**(1.285)**
Social	**-0.0254**	**-2.272** **	**-0.0241***	**-0.278**	**-0.0390***	**-0.731**	**-0.0782**	**1.296**
	(0.0322)	**(1.004)**	**(0.0127)**	**(0.356)**	**(0.0205)**	**(0.459)**	**(0.0513)**	**(1.251)**
Late	**0.0195**	**-1.416**	**-0.0328*** **	**-0.397**	**-0.0177**	**-0.466**	**-0.107** **	**-0.733**
	(0.0314)	**(0.991)**	**(0.0126)**	**(0.352)**	**(0.0207)**	**(0.467)**	**(0.0496)**	**(1.213)**
Penalty	**0.00236**	**-2.216** **	**-0.0456*** **	**-0.555**	**-0.0480** **	**-1.184** **	**-0.0877***	**-0.531**
	(0.0314)	**(0.991)**	**(0.0126)**	**(0.355)**	**(0.0206)**	**(0.462)**	**(0.0511)**	**(1.251)**
Constant	-0.0151	-2.664	0.154	10.66**	0.528	-5.538	-2.334	-58.65
	(0.267)	(8.162)	(0.225)	(4.874)	(0.339)	(9.654)	(3.754)	(91.07)
Controls	YES	YES	YES	YES	YES	YES	YES	YES
Library FE	YES	YES	YES	YES	YES	YES	YES	YES
R-squared	0.132	0.122	0.159	0.135	0.155	0.171	0.254	0.271
Number of users	1416	1331	7770	7473	2609	2540	410	406
H0: Reminder=Social (*p* -value)	0.307	0.1482	0.4261	0.4313	0.1652	0.8437	0.5725	0.2205
H0: Reminder=Late (*p* -value)	0.7132	0.5401	0.9099	0.6476	0.735	0.7098	0.2533	0.7151
H0: Reminder=Penalty (*p* -value)	0.8647	0.1601	0.3707	0.9935	0.0712	0.2422	0.4654	0.8441
H0: Late=Penalty (*p* -value)	0.587	0.4239	0.3031	0.6497	0.1492	0.1293	0.6946	0.8688
H0: Reminder=Social=Late=Penalty (*p* -value)	0.5592	0.4117	0.3953	0.8298	0.2312	0.4686	0.7188	0.3277
H0: Reminder=Social=Late=Penalty=0 (*p* -value)	0.7228	0.1156	0.0058	0.4999	0.1134	0.1405	0.2438	0.4837
Cross-Equation Joint Tests (*p* -values)	Prop. Late	"Actual - Due" Date						
H0: Reminder equal across age groups	0.4989	0.9895						
H0: Social equal across age groups	0.7738	0.0893						
H0: Late equal across age groups	0.1714	0.7127						
H0: Penalty equal across age groups	0.3788	0.2711						

Notes : The table reports treatment effects for different age groups. Page 1 of the table encompasses users in treatments Control-Reminder-Social, analogue to Table 5, and page 2 of the table corresponds to late users in treatments Control-Reminder-Social-Late-Penalty, analogue to Table 6. The full set of controls is used, as well as the library fixed effects. See the notes from previous tables. Robust standard errors in paranthesis. *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

Table 11
Differential Treatment Effect by Gender

	Control-Reminder-Social		**Control-Reminder-Social-Late-Penalty**	
	Proportion Late	"Actual - Due" Date	Proportion Late	"Actual - Due" Date
	(1)	(2)	(3)	(4)
Reminder	**-0.00770**	**-0.255**	**-0.0200**	**-0.302**
	(0.00945)	**(0.250)**	**(0.0134)**	**(0.368)**
Social	**-0.0207****	**-0.255**	**-0.0345*****	**-0.169**
	(0.00936)	**(0.247)**	**(0.0133)**	**(0.366)**
Late			**-0.0213**	**-0.0801**
			(0.0132)	**(0.363)**
Penalty			**-0.0475*****	**-0.915****
			(0.0132)	**(0.364)**
Male	0.00132	0.0613	-0.00120	0.382
	(0.0102)	(0.270)	(0.0144)	(0.394)
Reminder* Male	**-0.0141**	**-0.497**	**-0.00885**	**-0.721**
	(0.0145)	**(0.382)**	**(0.0203)**	**(0.557)**
Social*Male	**0.00552**	**-0.363**	**0.0110**	**-0.874**
	(0.0144)	**(0.379)**	**(0.0202)**	**(0.554)**
Late*Male			**-0.0134**	**-1.078***
			(0.0201)	**(0.551)**
Penalty*Male			**0.00979**	**0.0793**
			(0.0201)	**(0.553)**
Constant	0.375**	4.618	0.156	4.014
	(0.146)	(4.107)	(0.150)	(3.695)
Controls	YES	YES	YES	YES
Library FE	YES	YES	YES	YES
R-squared	0.166	0.138	0.161	0.135
Number of users	14442	13990	12205	11750
H0: Reminder=Social (*p* -value)	0.1689	0.9998	0.2812	0.7191
H0: Reminder=Late (*p* -value)			0.9244	0.5444
H0: Reminder=Penalty (*p* -value)			0.0395	0.0944
H0: Late=Penalty (*p* -value)			0.0462	0.0211
H0: Reminder=Social=Late=Penalty (*p* -value)			0.1278	0.0909
H0: Reminder=Social=Late=Penalty=0 (*p* -value)			0.0061	0.0882
H0: Reminder=Social=0 (*p* -value)	0.0818	0.4946		
H0: Reminder*Male=Social*Male(*p* -value)	0.1746	0.7253	0.3294	0.7839
H0: Reminder*Male=Late*Male(*p* -value)			0.8217	0.5183
H0: Reminder*Male=Penalty*Male(*p* -value)			0.3566	0.1491
H0: Late*Male=Penalty*Male (*p* -value)			0.2451	0.0347
H0: Reminder*Male=Social*Male=Late*Male=Penalty*Male (*p* -value)			0.5036	0.1643
H0: Reminder*Male=Social*Male=Late*Male=Penalty*Male=0 (*p* -value)			0.6721	0.1213
H0: Reminder*Male=Social*Male=0 (*p* -value)	0.3763	0.4016		

Notes : The table reports the differential treatment effect with respect to gender. *Male* is a dummy variable taking a value of 1 in case of male, and 0 in case of female. The full set of controls is used, as well as the library fixed effects. See the notes from previous tables. Robust standard errors in parantheses *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE 12
Treatment Effects by Nationality (Treatments Control-Reminder-Social)

	Proportion Late						
	Spain	**Northern-Central Europe**	**West-South Europe**	**English Speaking**	**Eastern-Russia**	**Latin America**	**Asia**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reminder	**-0.0111**	**-0.00536**	**-0.00472**	**-0.123****	**0.0915**	**-0.0254**	**-0.0666**
	(0.00839)	**(0.0550)**	**(0.0315)**	**(0.0558)**	**(0.0677)**	**(0.0180)**	**(0.102)**
Social	**-0.0148***	**-0.0456**	**0.00147**	**-0.207*****	**-0.0164**	**-0.0227**	**0.101**
	(0.00834)	**(0.0564)**	**(0.0310)**	**(0.0544)**	**(0.0661)**	**(0.0178)**	**(0.0869)**
Constant	0.260***	0.411***	0.280***	0.294**	0.182*	0.308***	-0.0764
	(0.0131)	(0.111)	(0.0816)	(0.116)	(0.101)	(0.0311)	(0.147)
Controls	YES	YES	YES	YES	YES	YES	YES
R-squared	0.152	0.126	0.190	0.261	0.226	0.167	0.413
Number of users	10395	265	745	224	185	2369	84
H0: Reminder=Social (*p*-value)	0.6576	0.4673	0.8416	0.145	0.0958	0.8786	0.0674
H0: Reminder=Social=0 (*p*-value)	0.1803	0.6758	0.9787	0.0008	0.2093	0.3006	0.1596
	"Actual - Due" Date						
	Spain	**Northern-Central Europe**	**West-South Europe**	**English Speaking**	**Eastern-Russia**	**Latin America**	**Asia**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reminder	**-0.373***	**-0.320**	**-0.708**	**-1.536**	**-1.367**	**-0.418**	**-0.546**
	(0.216)	**(1.138)**	**(0.907)**	**(2.002)**	**(1.784)**	**(0.513)**	**(1.983)**
Social	**-0.348**	**0.331**	**-0.271**	**-5.488*****	**-2.503**	**0.113**	**1.923**
	(0.215)	**(1.175)**	**(0.896)**	**(1.959)**	**(1.700)**	**(0.507)**	**(1.705)**
Constant	1.128***	-1.086	2.929	5.396	3.961	1.627*	-7.904***
	(0.327)	(2.435)	(2.310)	(4.047)	(2.442)	(0.863)	(2.664)
Controls	YES	YES	YES	YES	YES	YES	YES
R-squared	0.125	0.169	0.192	0.124	0.136	0.112	0.396
Number of users	10091	256	721	216	178	2284	82
H0: Reminder=Social (*p*-value)	0.9083	0.5692	0.6206	0.0586	0.5061	0.2899	0.1679
H0: Reminder=Social=0 (*p*-value)	0.1537	0.85	0.7322	0.0184	0.3405	0.541	0.306
Cross-Equation Joint Tests (*p*-values)	Prop. Late	"Actual-Due" Date					
H0: Reminder: (1)=(2)=...=(7)	0.3439	0.9874					
H0: Social: (1)=(2)=...=(7)	0.0401	0.0216					

TABLE 12 (continued)
Treatment Effects by Nationality (Control-Reminder-Social-Late-Penalty)

	Proportion Late						
	Spain	**Northern-Central Europe**	**West-South Europe**	**English Speaking**	**Eastern-Russia**	**Latin America**	**Asia**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reminder	**-0.0184**	**0.0258**	**0.0133**	**-0.224*** **	**0.0315**	**-0.0401***	**-0.206***
	(0.0123)	**(0.0669)**	**(0.0407)**	**(0.0690)**	**(0.0868)**	**(0.0236)**	**(0.111)**
Social	**-0.0253** **	**-0.0150**	**0.0139**	**-0.295*** **	**-0.0788**	**-0.0256**	**-0.0211**
	(0.0122)	**(0.0681)**	**(0.0393)**	**(0.0684)**	**(0.0825)**	**(0.0233)**	**(0.100)**
Late	**-0.0290** **	**0.0840**	**-0.0156**	**-0.186*** **	**0.0615**	**-0.0108**	**-0.207** **
	(0.0121)	**(0.0669)**	**(0.0396)**	**(0.0659)**	**(0.0820)**	**(0.0235)**	**(0.0994)**
Penalty	**-0.0427*** **	**0.0263**	**-0.0463**	**-0.245*** **	**-0.0659**	**-0.0111**	**-0.280*** **
	(0.0122)	**(0.0710)**	**(0.0387)**	**(0.0662)**	**(0.0825)**	**(0.0233)**	**(0.104)**
Constant	0.274***	0.299	0.217**	0.444***	0.112	0.361***	0.0430
	(0.0172)	(0.184)	(0.0927)	(0.124)	(0.115)	(0.0366)	(0.141)
Controls	YES	YES	YES	YES	YES	YES	YES
R-squared	0.144	0.261	0.195	0.286	0.273	0.156	0.519
Number of users	8198	241	778	230	195	2308	79
H0: Reminder=Social (*p* -value)	0.5771	0.542	0.9874	0.3284	0.1812	0.526	0.0762
H0: Reminder=Late (*p* -value)	0.3868	0.3648	0.4713	0.5823	0.7142	0.2024	0.9899
H0: Reminder=Penalty (*p* -value)	0.0494	0.9949	0.1281	0.7649	0.229	0.205	0.4926
H0: Late=Penalty (*p* -value)	0.2634	0.4005	0.4192	0.3804	0.0966	0.9886	0.4617
H0: Reminder=Social=Late=Penalty (*p* -value)	0.2495	0.513	0.3404	0.4623	0.1869	0.5271	0.0455
H0: Reminder=Social=Late=Penalty=0 (*p* -value)	0.0105	0.6246	0.4845	0.0002	0.3028	0.4686	0.0178
	"Actual - Due" Date						
	Spain	**Northern-Central Europe**	**West-South Europe**	**English Speaking**	**Eastern-Russia**	**Latin America**	**Asia**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Reminder	**-0.413**	**0.750**	**0.174**	**-6.450*** **	**-2.588**	**-0.797**	**-1.796**
	(0.332)	**(1.764)**	**(1.082)**	**(2.341)**	**(2.457)**	**(0.689)**	**(2.344)**
Social	**-0.343**	**2.613**	**0.138**	**-8.512*** **	**-4.938** **	**-0.373**	**2.943**
	(0.332)	**(1.792)**	**(1.051)**	**(2.333)**	**(2.298)**	**(0.679)**	**(2.104)**
Late	**-0.638***	**3.497** **	**-0.0316**	**-7.432*** **	**-1.902**	**0.605**	**-1.128**
	(0.329)	**(1.748)**	**(1.060)**	**(2.239)**	**(2.294)**	**(0.683)**	**(2.079)**
Penalty	**-0.823** **	**2.547**	**-1.331**	**-7.085*** **	**-5.103** **	**-0.0294**	**-2.397**
	(0.331)	**(1.861)**	**(1.040)**	**(2.219)**	**(2.317)**	**(0.684)**	**(2.157)**
Constant	1.676***	0.0302	-1.796	12.88***	3.520	2.639***	-5.836**
	(0.428)	(5.358)	(2.456)	(4.090)	(2.960)	(1.008)	(2.813)
Controls	YES	YES	YES	YES	YES	YES	YES
R-squared	0.112	0.182	0.206	0.166	0.198	0.130	0.442
Number of users	7902	237	747	217	184	2222	78
H0: Reminder=Social (*p* -value)	0.8333	0.2919	0.9723	0.4045	0.3164	0.522	0.0337
H0: Reminder=Late (*p* -value)	0.5006	0.107	0.8453	0.6784	0.7716	0.0354	0.7716
H0: Reminder=Penalty (*p* -value)	0.2208	0.3335	0.1445	0.7911	0.2823	0.2501	0.793
H0: Late=Penalty (*p* -value)	0.5761	0.5954	0.1977	0.8795	0.1428	0.3384	0.5347
H0: Reminder=Social=Late=Penalty (*p* -value)	0.4617	0.4398	0.3817	0.8641	0.3634	0.1894	0.0361
H0: Reminder=Social=Late=Penalty=0 (*p* -value)	0.1299	0.2526	0.5274	0.0015	0.1475	0.3041	0.0694
Cross-Equation Joint Tests (*p* -values)	Prop. Late	"Actual-Due" Date					
H0: Reminder: (1)=(2)=…=(7)	0.0905	0.1302					
H0: Social: (1)=(2)=…=(7)	0.0256	0.001					
H0: Late: (1)=(2)=…=(7)	0.0938	0.003					
H0: Penalty: (1)=(2)=…=(7)	0.0355	0.0064					

Notes : The table reports treatment effects for different groups of nationalities. The first page encompasses the users in treatments Control-Reminder-Social, analogue to Table 5 and the second page corresponds to the users in treatments Control-Reminder-Social-Late-Penalty, analogue to Table 6. Robust standard errors in parantheses *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE A.1
Prop. of Late Returns for Different Nationality Groups

	Prop. Late Before (1)	Prop. Late After (2)
Europe-North-Central	**-0.0137**	**-0.0109**
	(0.0111)	**(0.0172)**
Europe-West-South	**0.0245***	**0.0347***
	(0.00708)	**(0.0105)**
English Speaking Countries	**0.0369***	**0.0438**
	(0.0116)	**(0.0178)**
Russia-East	**0.0076**	**0.0453**
	(0.0130)	**(0.0192)**
Latin America	**0.0292***	**0.0552***
	(0.00436)	**(0.0064)**
Asia	**-0.0608***	**-0.01678**
	(0.0175)	**(0.0283)**
Constant	0.4115***	0.2977**
	(0.0131)	(0.1294)
Controls	YES	YES
Library FE	YES	YES
R-squared	0.0449	0.092
Number of users	59367	25591
H0: Nationality groups equal	0	0.0014
H0: Nationality groups equal=0	0	0

Notes : The table reports proportion of late returns per user for different groups of nationalities. The omitted variable is Spaniards. Column (1) refers to the pre-treatment period and column (2) to the post-treatment period. Full set of controls is used. Robust standard errors in parantheses *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE A.2
English Speaking Countries compared to Spain

	Prop. Late (1)	"Actual - Due" Date (2)	Prop. Late (3)	"Actual - Due" Date (4)
Reminder	-0.00797	-0.469**	-0.00221	-0.309
	(0.0112)	(0.218)	(0.0230)	(0.336)
Social	-0.0112	-0.372*	-0.0308	-0.390
	(0.0111)	(0.218)	(0.0230)	(0.336)
Late			-0.0526**	-0.642*
			(0.0229)	(0.334)
Penalty			-0.0451**	-0.833**
			(0.0227)	(0.336)
English	0.149***	3.579***	0.183***	6.264***
	(0.0386)	(0.999)	(0.0504)	(1.370)
Reminder*English	**-0.117****	**-1.543**	**-0.184****	**-5.626*****
	(0.0574)	**(1.494)**	**(0.0751)**	**(2.050)**
Social*English	**-0.195*****	**-4.892*****	**-0.255*****	**-7.623*****
	(0.0566)	**(1.470)**	**(0.0741)**	**(2.035)**
Late*English			**-0.148****	**-7.308*****
			(0.0706)	**(1.942)**
Penalty*English			**-0.223*****	**-6.586*****
			(0.0721)	**(1.963)**
Prior Late	0.319***		0.277***	
	(0.0173)		(0.0277)	
Prior "Actual - Due"		0.209***		0.193***
		(0.0191)		(0.0264)
Reminder*Prior Late	-0.0124		-0.0343	
	(0.0247)		(0.0393)	
Social*Prior Late	-0.0158		0.00553	
	(0.0246)		(0.0393)	
Reminder*Prior "Actual - Due"		-0.0571**		-0.0933***
		(0.0258)		(0.0340)
Social*Prior "Actual - Due"		0.0185		-0.0427
		(0.0276)		(0.0375)
Late*Prior Late			0.0445	
			(0.0389)	
Penalty*Prior Late			-0.00215	
			(0.0386)	
Late*Prior "Actual - Due"				-0.0503
				(0.0347)
Penalty*Prior "Actual - Due"				-0.0816**
				(0.0379)
Constant	0.332	3.382	0.164	-0.333
	(0.208)	(5.707)	(0.215)	(6.254)
Controls	YES	YES	YES	YES
Library FE	YES	YES	YES	YES
R-squared	0.161	0.137	0.156	0.131
Number of users	10619	10307	8428	8119

Notes: The table reports differential treatment effects for users from the English speaking countries. The reference group is Spaniards (omitted). Interaction terms for differential treatment effects for users in the English speaking countries are shown. Interaction terms for differential treatment effects based on the behavior prior to the treatment are included. Full set of controls, as well as library fixed effects are included. See the notes from previous tables. Robust standard errors in parantheses *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.

TABLE A.3
Asia compared to Spain

	Prop. Late (1)	"Actual - Due" Date (2)	Prop. Late (3)	"Actual - Due" Date (4)
Reminder	-0.00642	-0.471**	0.00319	-0.310
	(0.0112)	(0.216)	(0.0232)	(0.334)
Social	-0.0113	-0.373*	-0.0297	-0.396
	(0.0111)	(0.216)	(0.0232)	(0.334)
Late			-0.0430*	-0.652**
			(0.0231)	(0.332)
Penalty			-0.0411*	-0.839**
			(0.0229)	(0.334)
UKA-USA	-0.0374	-1.393	0.0860	-0.246
	(0.0746)	(1.888)	(0.0974)	(2.580)
Reminder*Asia	**-0.110**	**-0.759**	**-0.267***	**-2.578**
	(0.105)	**(2.699)**	**(0.141)**	**(3.808)**
Social*Asia	**0.124**	**2.217**	**-0.00630**	**1.402**
	(0.0929)	**(2.361)**	**(0.129)**	**(3.429)**
Late*Asia			**-0.194**	**-1.744**
			(0.126)	**(3.351)**
Penalty*Asia			**-0.264****	**-2.815**
			(0.128)	**(3.386)**
Prior Late	0.320***		0.283***	
	(0.0174)		(0.0280)	
Prior "Actual - Due"		0.204***		0.191***
		(0.0191)		(0.0265)
Reminder*Prior Late	**-0.0180**		**-0.0452**	
	(0.0249)		**(0.0396)**	
Social*Prior Late	**-0.0162**		**0.00391**	
	(0.0248)		**(0.0397)**	
Reminder*Prior "Actual - Due"		**-0.0564****		**-0.0940*****
		(0.0255)		**(0.0338)**
Social*Prior "Actual - Due"		**0.0215**		**-0.0390**
		(0.0275)		**(0.0375)**
Late*Prior Late			**0.0258**	
			(0.0392)	
Penalty*Prior Late			**-0.00934**	
			(0.0390)	
Late*Prior "Actual - Due"				**-0.0422**
				(0.0352)
Penalty*Prior "Actual - Due"				**-0.0763****
				(0.0378)
Constant	0.329	3.295	0.158	-0.454
	(0.208)	(5.657)	(0.215)	(6.216)
Controls	YES	YES	YES	YES
Library FE	YES	YES	YES	YES
R-squared	0.159	0.137	0.155	0.131
Number of user	10479	10173	8277	7980

Notes: The table reports differential treatment effects for Asian users. The reference group is Spaniards (omitted). Interaction terms for differential treatment effects for Asia are shown. Interaction terms for differential treatment effects based on the behavior prior to the treatment are included. Full set of controls, as well as library fixed effects are included. See the notes from previous tables. Robust standard errors in parantheses *: significant at the 10% level; **: significant at the 5% level; ***: significant at the 1% level.