Oops!... I Did It Again: Understanding Mechanisms of Persistence in Prosocial Behavior*

Adrian Bruhin[a] Simon Haenni[b] Lingqing Jiang[c]
Adrian Roethlisberger[d] Regual Buchli[d] Beat M. Frey[d]
Lorenz Goette[e,f]

2022-02-17

Abstract

We test whether asking individuals to donate blood leads to a persistent change in behavior, and examine the underlying mechanism. In a field experiment, we randomize a phone call, asking blood donors to turn out, and follow them over up to 18 months. We observe significant behavioral persistence for at least one year. We use naturally occurring rainfall as a second instrument for donor turnout to test whether behavioral persistence is due to habit formation (Stigler and Becker, 1977) or a persistent increase in motivation independent of past donation. Our results strongly favor habit formation as the underlying mechanism.

Keywords: Prosocial behavior, Habit formation, Field experiment, Natural experiment

JEL Classification: C93, D04, D91, C36

*We gratefully acknowledge financial support from the Swiss national Science Foundation (Grant # 141767), the Deutsche Forschungsgemeinschaft (DFG) through CRC TR 224 (Project B07) and Germany's Excellence Strategy EXC 2126/1 390838866, the BA Leverhulme Small Research Grants (SRG20/201230), and the Essex International Visiting Fellowships. **Authors' affiliation**: [a] University of Lausanne, Faculty of Business and Economics (HEC Lausanne), 1015 Lausanne, Switzerland; [b] University of Zurich, Department of Economics, 8001 Zurich, Switzerland; [c] University of Essex, Department of Economics, Colchester CO4 3SQ, UK [d] Blutspende Zürich, 8952 Schlieren [e] National University of Singapore, Department of Economics, Singapore, and University of Bonn, Department of Economics, 53113 Bonn, Germany; **Author contributions:** AB, BF, LG conceived and designed the study; BF oversaw the data collection; SH, LJ analyzed the data; AB, BF, LG, SH, LJ wrote the paper. **Corresponding Author**: Adrian Bruhin, University of Lausanne, 1015 Lausanne, Switzerland; email: adrian.bruhin@unil.ch; phone: +41 (0) 692 34 86

1 Introduction

Continued engagement in prosocial behavior is essential for the formation of social capital (Putnam 1995). Examples include complying with laws, volunteering, donating to charities, voting, and donating blood. Hence, there is an interest in studying policy interventions that can make such behaviors persistent. Several studies revealed how standard tools, such as price incentives, can induce behavioral change beyond the period during which incentives are used.[1]

More recently, behavioral interventions have become popular as policy tools (Obama 2015). Several examples showed them to be equally, if not more effective than standard interventions (Benartzi et al. 2017). A particularly successful example is making a direct ask to elicit prosocial behavior (Freeman 1997; Andreoni and Rao 2011; Andreoni, Rao and Trachtman 2017; Milkman et al. 2011, 2012; Adena and Huck 2020). Other examples include providing feedbacks (Byrne et al. 2019; Hussam et al. 2022) and making behavior visible (Gerber, Green and Shachar 2003).

Yet, there is little evidence whether such interventions have persistent effects on behavior, and what the underlying behavioral mechanisms might be. On the one hand, persistence may arise due to habit formation in the sense of Stigler and Becker (1977), where engaging in a prosocial activity in the past increases the utility of engaging in the same activity today. On the other hand, persistence may also arise if the intervention increases the individuals' motivation to engage in the prosocial activity over several periods, irrespective of whether they have engaged in the activity in the past or not. For instance, because it highlights the social returns of the activity.

Discriminating between these two mechanisms is important since they can have distinct welfare implications (Aronsson and Löfgren 2008). Habit formation is welfare-neutral if individuals internalize that engaging in the prosocial activity will increase their marginal utility in the future. In contrast, persistent changes in motivation alter welfare. For example, a onetime intervention that generates social pressure to engage in a prosocial activity may lower individuals' utility in every period they do not engage in it.

In this paper, we study whether asking individuals to donate blood leads to a persistent change in that behavior, and whether this change results from habit formation or a persistent increase in the donors' motivation. Voluntary blood donations are a textbook example of an

[1]For instance, Charness and Gneezy (2009) and Acland and Levy (2015) pay individuals to exercise in the gym; Loewenstein, Price and Volpp (2016) provide children small financial incentives to eat fruits or vegetables; Yang and Lim (2017) rebates subway tickets to shift commuters to off-peak times. Some interventions, such as matching donations, have also been shown to lead to the opposite effect and decrease subsequent donations (Meier 2007).

important prosocial behavior in the real world. Donating blood entails substantial personal costs in terms of time and discomfort, but benefits a large number of anonymous recipients. Moreover, most developed countries rely exclusively on voluntary blood donations (World Health Organization 2011), making effective interventions particularly relevant.

We present a theoretical framework that formalizes how habit formation and changes in the donors' motivation can lead to persistence in voluntary blood donations. In our framework, the utility from a present donation depends on two components. The first component represents habit formation. It features a habit formation parameter, γ, to quantify the extent to which past donations increase the marginal utility from present donations. The second component represents the donors' motivation. It does not depend on previous donations and initially corresponds to a baseline level. However, it may react to policy interventions as well, for instance, if donors learn about the social returns of donating after being treated. The framework defines our empirical strategy to discriminate between the two mechanisms.

We conduct a field experiment among voluntary blood donors at the Blood Transfusion Service of the Red Cross in Zurich, Switzerland (BTSRC). All donors donated at least once before the onset of the study. Every six months, they receive a letter inviting them to an upcoming blood drive on a specific date. Moreover, they also receive a text message on their mobile phone as a reminder one day before the blood drive they were invited to takes place. We track the behavior of these donors over four invitation periods of six months.

The field experiment focuses on a subset of 1400 inactive donors who did not show up at any blood drive they were invited to for at least one year before the onset of the study.[2] We randomly assign each of these inactive donors to one of four experimental conditions. The intervention is to ask donors via phone to commit to participating in the blood drive two days from now. Donors in conditions C1 and C2 receive only one phone call and are asked to donate in period 1 and 2, respectively. Donors in condition C12 receive two phone calls and are asked to donate in, both, periods 1 and 2. Donors in the control condition do not receive any phone call. The random variation in the intervention allows us to isolate its effects on behavioral persistence from other causes of serial correlation in donation rates, such as unobserved changes in the environment.

The reduced-form evidence indicates that the intervention has a persistent positive effect on donation rates for at least one year. Asking donors to make a donation at the upcoming

[2]Inactive donors are of particular interest to the BTSRC for three reasons. First, focusing on inactive donors mitigates the potential risk of crowding out intrinsic motivation of highly active donors (Bruhin et al. 2015). Second, the maximum permitted frequency of donating blood every three-four month does not constrain inactive donors. Third, inactive donors make up the majority of the potential donor pool, accounting for 60% of all registered donors at any given time while more than 80% of donors are inactive at least for some period.

blood drive increases their probability to donate by 18 to 26 percentage points, depending on the specification ($p < 0.01$ in all specifications). The impact of the intervention persists over time: six months later, the probability to donate is still 8 to 17 percentage points higher ($p < 0.01$); twelve months later, it is 5 to 13 percentage points higher ($p < 0.05$). Thus, asking leads to an increase in the donation rate that lasts for at least one year.

Next, we explore whether the mechanism behind the persistence in blood donations is habit formation or an increase in the donors' motivation that does not depend on pervious donations. Note that using the intervention as the sole instrument does not allow us to distinguish between the two mechanisms as receiving a phone call could lead to habit formation as well as learning about the social returns of donating blood. More formally, if both mechanisms were at work, the intervention would violate the exclusion restriction and, thus, be invalid as an instrument for habit formation.

Testing the exclusion restriction requires a second instrument that only affects the donors' current probability to donate, but not their future motivation. To obtain such a second instrument, we exploit a natural experiment relying on random fluctuations in rainfall on the days of the different blood drives.[3] We collect the data on rainfall from the Swiss Federal Office of Meteorology and Climatology. We use an indicator of strong rainfall on the days of the blood drives as the second instrument for future donations. The indicator for strong rainfall has three key characteristics. First, it exogenously adds a temporary extra cost to donating blood at affected blood drives, e.g., by increasing the duration and discomfort of the commute. Second, rainfall today plausibly leaves the motivation to donate blood six months later unaffected. Third, the indicator for strong rainfall is orthogonal to the intervention, which is balanced within blood drives.

We identify the mechanism behind the persistence in blood donations by exploiting the changes in the donation rate caused by random fluctuations in strong rainfall as a benchmark. That is, we carry out an overidentification test relying on the following intuition: if the intervention of asking donors to make a donation at the upcoming blood drive satisfies the exclusion restriction, then we should find similar estimates of persistence, regardless of whether we include the indicator for a donor being asked, the indicator for strong rainfall on the day of the blood drive, or both indicators among the instruments. However, if the intervention had a positive (negative) direct effect on future motivation, then the estimated persistence in blood donations would be larger (smaller) when we use the indicator for a donor being asked as an instrument.

[3]Rainfall has been used as exogenous shock in several contexts in the economics literature (e.g. Miguel, Satyanath and Sergenti 2004; Maccini and Yang 2009; Brückner and Ciccone 2011). In a setting similar to ours, Fujiwara, Meng and Vogl (2016) use daily rainfall on election days as a cost shock.

The overidentification test does not reject the null hypothesis that both indicators are valid instruments ($p = 0.8$). That is, we obtain similar estimates regardless of which of the instruments we use. Therefore, we conclude that asking donors leads to a persistent increase in donation rates through habit formation. We also replicate the same analysis in a larger sample that implements a slightly different intervention. The intervention also asks donors to make a donation via a phone call. However, instead of being fully randomized, the phone call is triggered by a temporary shortage in certain blood types. Nevertheless, when we apply the overidentification test in this larger sample over an entirely different sample period, we arrive at the same conclusion: the estimate for the persistence in blood donations remains similar, and using rainfall as a second instrument shows no indication of failure of the exclusion restriction.

Having ruled out persistent changes in the donors' motivation as a potential channel, we impose the structure of our theoretical framework to estimate the habit formation parameter γ. Our most conservative estimate of γ is 0.484 ($p < 0.001$). That is, asking increases the donation rate not only by 18 percentage points in the present period, but also in all future periods: by $0.484 \cdot 0.18 = 9$ percentage points six months later, by $0.484^2 \cdot 0.18 = 4$ percentage points one year later, and so on.

Our study extends three strands of literature. First, it contributes to an emerging strand of literature examining habit formation in various behaviors. Most of the evidence on habit formation comes from daily activities such as food consumption (Naik and Moore 1996; Fuhrer 2000; Carrasco, Labeaga and Lopez-Salido 2005), energy and water consumption (Allcott and Rogers 2014; Byrne et al. 2019), and handwashing (Hussam et al. 2022; Steiny Wellsjo 2021). More closely related to our setup are studies of persistence in voting. Gerber, Green and Shachar (2003) observe in a field experiment that urging registered voters to participate in the current election through direct mail or face-to-face canvassing increases turnout in the next election. Fujiwara, Meng and Vogl (2016), however, point out that this observed persistence in voting could be driven by a shift in voters' motivation rather than by habit formation. Similar to our study, they exploit random fluctuations in regional rainfall patterns as the instrument for voting, and still find strong evidence of persistence. Our study contributes to this literature by proposing an explicit test of whether an intervention affects future behavior through habit formation or via a persistent change in the underlying motivation: it combines experimental variation at the individual level with regional and temporal variation in rainfall to perform an overidentification test.[4]

[4]The mechanism of habit formation in our setup is also in line with consistency-based compliance discussed in the psychology literature (Freedman and Fraser 1966; Cialdini, Trost and Newsom 1995; Cialdini and Trost 1998; Cialdini and Goldstein 2004). This literature suggests that individuals have a need to maintain a positive self-concept and act consistently with their self-views and prior commitments in order to serve the

Second, our paper contributes to the strand of literature that analyzes persistent effects of interventions on prosocial behavior.[5] This literature has focused primarily on charitable donations. Meer (2013) shows that there is persistence in donations to universities, using their football team's past success as an instrument. Landry et al. (2006) provide lottery incentives to charity donors in a field experiment. They notice that the long-run effect of such an incentive on donations depends on whether the lottery signals good quality of the charity. In a related study, Landry et al. (2010) compare the effects of a door-to-door fund raiser, a small gift, and a large gift on charitable donations. The study finds that donors initially attracted by features that signal charitable quality are weakly more loyal in the future than donors attracted by a simple ask for money. Meier (2007) investigates the effects of matching charitable donations in a field experiment. He finds that donations increase while being matched but drop below the baseline after the matching ends – suggesting that such incentives can undermine the donors' intrinsic motivation. Adena and Huck (2019) find that while anticipating a future fundraising letter reduces the current donation, the future donation is higher if a donation was made in the current period, which suggests that habit formation may play an role. Thus, studies of charitable donations find little evidence of habit formation when using experimental variation.

Few studies have examined persistence in other prosocial behaviors. Lacetera, Macis and Slonim (2014) and Goette and Stutzer (2020) examine the persistence of monetary incentives to donate blood. Even though incentives lead to higher donations, neither study finds that the treatment effect persists once the incentives are removed. However, as Adena and Huck (2019) suggest, it is possible that the null effect is due to crowding-out of intrinsic motivation and habit formation pulling in opposite directions. Our paper contributes to this literature by using a behavioral intervention – making an ask – rather than monetary incentives to encourage donations. It provides evidence of habit formation in a costly prosocial behavior such as blood donations.

At first glance, our results are surprising in light of the literature on moral licensing indicating that there is intertemporal substitution in moral or prosocial behaviors (Merritt, Effron and Monin 2010). However, Gneezy et al. (2012) suggest that costly prosocial be-

ultimate motivation of maintaining or enhancing their self-esteem. This preference for consistency would make a future blood donation more desirable for individuals who donated already in the past. Interestingly, in contrast to the view in the psychological literature on habit formation that habit formation requires frequent repetition of the behavior (Wood and Neal 2007; Wood and Rünger 2016), we find evidence for habit formation in voluntary blood donations after a one-time intervention – a behavior that can be repeated at most every three months.

[5] Handwashing (Hussam et al. 2022; Steiny Wellsjo 2021) and voting (Gerber, Green and Shachar 2003; Fujiwara, Meng and Vogl 2016) also have a prosocial component. However, they may be partially driven by selfish motives to protect one's own health, or promote one's own political goals. Moreover, they are arguably much less costly than donating blood.

haviors serve as a signal of prosocial identity and that people subsequently behave in line with that self-perception. In contrast, costless prosocial acts do not signal much about one's prosocial identity, and therefore, subsequent behavior is less likely to be consistent and may even show the reductions in prosocial behavior associated with licensing. Our findings in blood donation – a costly prosocial behavior – confirm their account.

Finally, our study also contributes to the strand of literature on voluntary blood donations. Recent papers have mainly focused on the role of incentives (Goette and Stutzer 2020; Goette et al. 2009; Lacetera, Macis and Slonim 2012a, 2013) and social interactions among blood donors (Bruhin et al. 2020). We show that, by exploiting the tendency to form habits in relatively unmotivated donors, blood donation services could make their interventions to manage donor turnout more effective.

The paper is organized as follows. Section 2 illustrates the theoretical framework incorporating the two mechanisms that could be behind the persistence in blood donations. Section 3 describes the experimental setup and data. Section 4 presents the reduced form evidence. Section 5 disentangles the two mechanisms and replicates our findings in a larger sample exploiting a quasi-experiment with a similar intervention. Section 6 structurally estimates the habit formation parameter. Section 7 concludes the paper.

2 Mechanisms behind Behavioral Persistence

This section discusses the two potential mechanisms – habit formation and changes in the donors' future motivation – which may lead to behavioral persistence.

2.1 Theoretical Framework

In our theoretical framework, a donor's contemporaneous utility of donating blood in period t is a function of whether she donates in the current period, d_t, two components, S_t and B, and a random cost shock, $\tilde{c}_t$:

$$u_t = u(d_t, S_t, B, \tilde{c}_t). \tag{2.1}$$

The first component, S_t, represents habit formation. The second component, B, represents the donor's baseline motivation to donate, which does not depend on previous donations but may, nevertheless, be influenced by policy interventions. The random cost shock, $\tilde{c}_t$, follows a distribution with cdf F_c. Time is discrete as in the model of habit formation by Stigler and Becker (1977), and we abstract from discounting.

2.1.1 Habit Formation

The donor's contemporaneous utility in period t can be expressed as

$$u(d_t, S_t, B, \tilde{c}_t) = \begin{cases} \gamma S_t + B - \tilde{c}_t & \text{if } d_t = 1 \\ 0 & \text{if } d_t = 0 \end{cases}, \tag{2.2}$$

where S_t depends on the donation in the last period, $S_t = d_{t-1}$. It corresponds to the habit stock in the model of Stigler and Becker (1977) with the habit stock fully depreciating after one period. The habit formation parameter, γ, governs the extent to which previous donation increases the marginal utility of present donation. The donor makes a donation in period t if

$$u(d_t = 1) - u(d_t = 0) = \gamma S_t + B - \tilde{c}_t = \gamma d_{t-1} + B - \tilde{c}_t \geq 0. \tag{2.3}$$

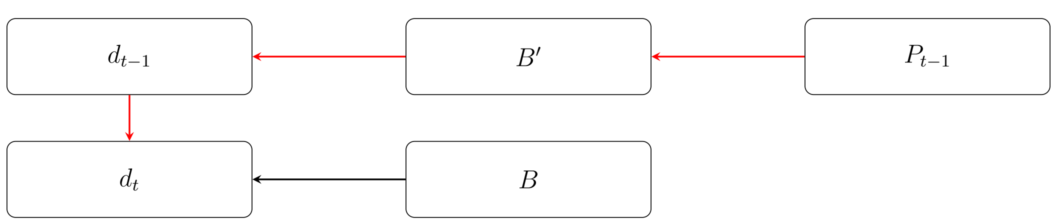
As $\tilde{c}_t$ is a random cost shock, the probability of donating in period t is given by

$$Pr(d_t = 1) = Pr(\tilde{c}_t \leq \gamma d_{t-1} + B) = F_c(\gamma d_{t-1} + B). \tag{2.4}$$

Since the donors in our sample did not donate in the year before they entered our study, $d_0 = 0$ and, thus, $S_1 = 0$ for all donors.

Figure 1 illustrates how a policy intervention in period $t-1$, P_{t-1}, may lead to behavioral persistence in blood donations through habit formation. First, the intervention temporarily increases the donor's motivation from the baseline level B to B' in period $t-1$, which leads to a donation in $t-1$, d_{t-1}. Subsequently, the donation d_{t-1} increases the probability to donate in the following period t, even when the donor's motivation falls back to the baseline level, B.[6]

Figure 1: Persistence through habit formation



[6]Alternatively, the policy intervention could also temporarily lower the cost $\tilde{c}_t$ of donating.

2.1.2 Changes in Motivation

Even in the absence of habit formation, a policy intervention can lead to behavioral persistence. In particular, a policy intervention may directly increase the donor's motivation over several periods. The policy intervention may directly increase the donor's motivation over several periods, for instance, if it highlights the social returns of the activity that may have been unknown to the individual, or leads to a persistent increase in attention to it (Camerer, Landry and Webb 2020; Steiny Wellsjo 2021).

Figure 2: Persistence through changes in future B

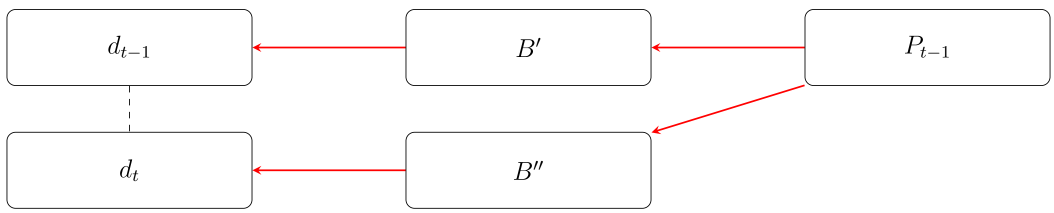


Figure 2 demonstrates this mechanism. The policy intervention in period $t-1$, P_{t-1}, increases the donor's motivation from the baseline level B to B' which leads to a donation in $t-1$, d_{t-1}. Since the change in the donor's motivation persists over several periods, the donor's motivation B'' is still at a higher level than B in the following period t, which directly affects the probability to donate in t as well.

3 Experimental Setup and Data

This section discusses the experimental setup and the data. We first outline the relevant procedures at the BTSRC, where our study took place. We then describe the field experiment, which relies on an intervention asking donors via phone to donate at the upcoming blood drive, and perform randomization checks. Finally, we discuss the natural experiment, which relies on random fluctuations in rainfall.

3.1 Background

To ensure a stable supply of whole blood transfusions, the BTSRC follows a multi-stage invitation procedure for its blood drives. Blood drives are regular events where donations can be made. They take places twice per year and are sponsored by local organizations, such as church chapters or sports clubs, while the BTSRC invites the donors and provides equipment and personnel. For each blood drive, the BTSRC first sends an invitation letter to all eligible donors, informing them about the event and highlighting the general benefits of blood donations for society. One day before the blood drive, it also sends a text message to all invited donors, reminding them about the time and the location of the event.

Our study focuses on 1400 inactive donors who did not show up at any blood drive they were invited to for at least one year before the onset of the study, and whose blood types are O+, O-, or A-.[7] Inactive donors are of particular interest to the BTSRC for three reasons. First, focusing on inactive donors mitigates the potential risk of crowding out intrinsic motivation. Second, the maximum permitted frequency of donating blood at most every three months does not constrain inactive donors at the beginning of the study. Third, inactive donors make up the majority of the pool, accounting for 60% of all registered donors at any given time. Furthermore, more than 80% of the donors are inactive at least for some period.

3.2 Field experiment

We now turn to the field experiment that allows us to analyze whether there is behavioral persistence in blood donations.

3.2.1 Intervention

The randomized intervention is delivered by a phone call: the BTSRC calls donors two days before the upcoming blood drive they have been invited to and asks them to make a donation. The phone call makes a strong ask: *"Can I put you down as attending our blood drive in two days?"* At the end of the phone call, the staff records whether the donor was reached and the extent of his or her commitment. Figure 3 illustrates the timing of the intervention along with the standard invitation procedure.

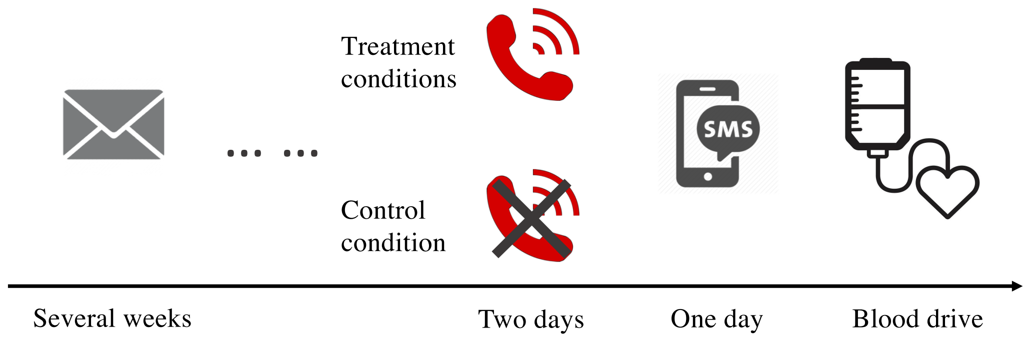
3.2.2 Implementation

We implemented the field experiment between March 2015 and December 2016. During this period, each local sponsor organized four blood drives, dividing our experiment into four periods of six months. We randomized the intervention within blood drive strata and defined four experimental conditions. Each condition comprises 350 of the 1400 inactive donors.

Table 1 summarizes the schedule of the intervention across the four experimental conditions. In the first condition, C1, donors receive a phone call only in period 1. In the second condition, C2, donors receive a phone call only in period 2, i.e., six months after the donors

[7] Other blood types are less useful to the BTSRC due to compatibility patterns. Thus, they were not targeted by the intervention.

Figure 3: Timing of the intervention (time before blood drive)



Notes: The intervention asks invited donors via a phone call to make a donation. It takes place two days before the upcoming blood drive, between the invitation letter and the text message reminder.

in condition C1. In the third condition, C12, donors receive a phone call in both periods 1 and 2, which allows us to test whether there is any interaction effect between two phone calls. In the control condition, donors do not receive any phone calls. There are no further phone calls in periods 3 and 4, i.e., 12 and 18 months later. However, we keep observing donation outcomes in periods 3 and 4.

Table 1: Intervention across experimental conditions

	Period 1 (t_1)	Period 2 (+6 months)	Period 3 (+12 months)	Period 4 (+18 months)	Number of individuals
Condition C1	Call	No Call	No Call	No Call	350
Condition C2	No Call	Call	No Call	No Call	350
Condition C12	Call	Call	No Call	No Call	350
Control Condition	No Call	No Call	No Call	No Call	350

Note: All donors receive a postal invitation to the blood drive they are registered in each period. One day before the blood drive, all donors receive an additional text message reminder (Standards invitation procedure at BTSRC).

3.2.3 Randomization Checks

Table 2 presents the randomization checks of the intervention. Columns (1)-(4) show the means and standard deviations of the donors' age, gender, and blood types across the four experimental conditions. Column (5) reports the p-values of the joint F-tests for equality in means across the four conditions. As none of the F-tests indicates a significant difference in means, we conclude that the randomization of the intervention succeeded.

Table 2: Randomization checks

	(1) Condition C1	(2) Condition C2	(3) Condition C12	(4) Control	(5) F-test (p-val.)
Age	41.140	40.226	42.051	41.126	0.36
	(13.171)	(13.373)	(13.984)	(13.544)	
Male	0.506	0.483	0.511	0.546	0.42
	(0.501)	(0.500)	(0.501)	(0.499)	
O+ blood type	0.826	0.817	0.820	0.829	0.98
	(0.380)	(0.387)	(0.385)	(0.377)	
O- blood type	0.054	0.083	0.057	0.046	0.19
	(0.227)	(0.276)	(0.232)	(0.209)	
A- blood type	0.120	0.100	0.123	0.126	0.71
	(0.325)	(0.300)	(0.329)	(0.332)	
Observations	350	350	350	350	1400

Notes: Means with standard deviations in parentheses.

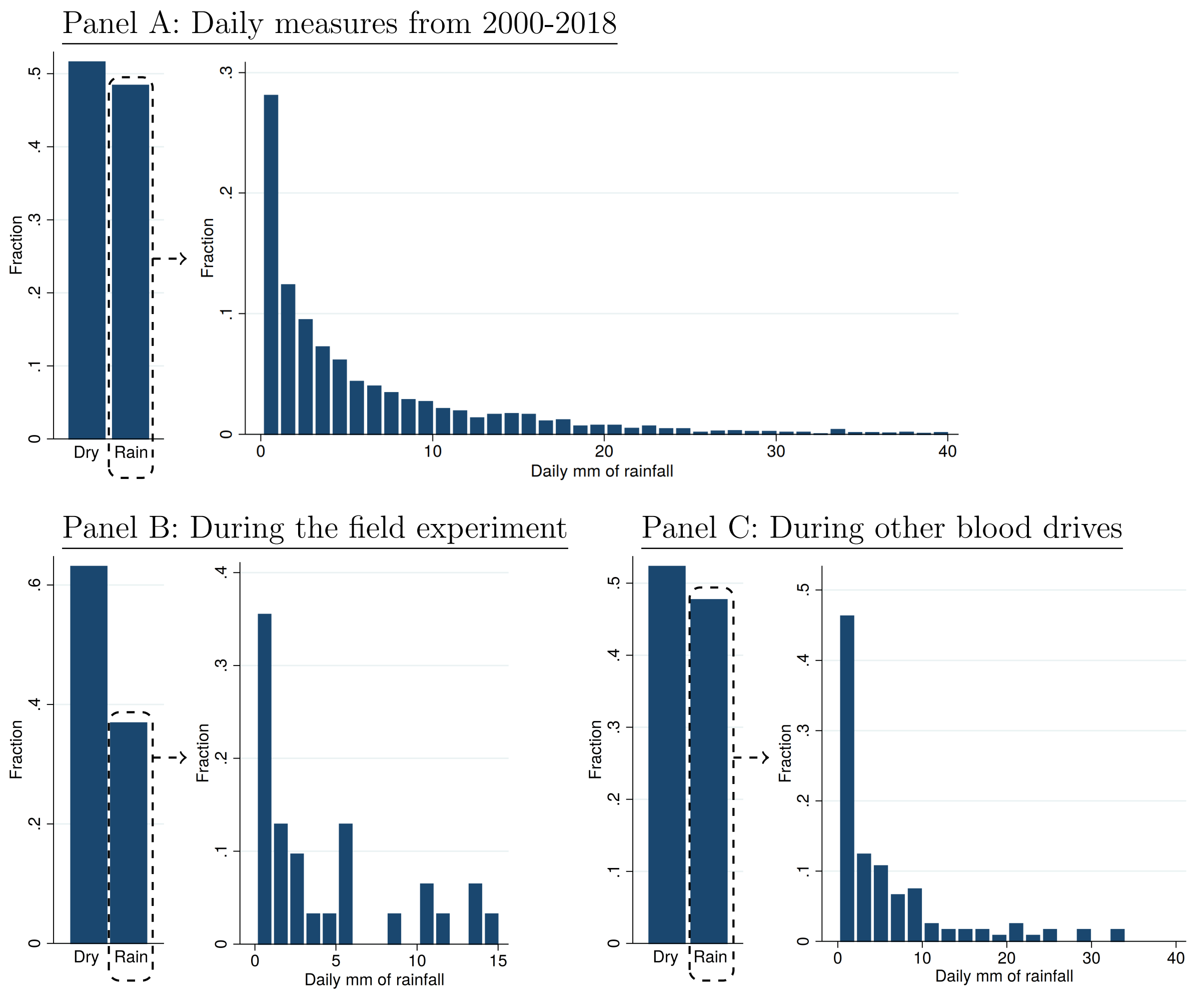
3.3 Natural Experiment

Next, we turn to the natural experiment to discriminate whether the behavioral persistence in blood donations is due to habit formation or persistent changes in the donors' motivation. The natural experiment relies on random fluctuations in daily rainfall which will allow us to construct a second instrument to isolate the effect of habit formation.

3.3.1 Descriptive Statistics

We first describe the random fluctuations in daily rainfall in the greater Zurich region. Figure 4 shows the measures of daily rainfall provided by the Swiss Federal Office of Meteorology and Climatology. Panel A shows the distribution of daily rainfall between 2000 and 2018. Almost half of the days exhibit some rainfall. Light rainfall with less 10mm of daily precipitation is particularly common, while strong rainfall exceeding 10mm of daily precipitation is rare. Panel B exhibits the distribution of daily rainfall on the days of the blood drives in our field experiment. There are fewer days with rainfall during the field experiment than between 2000 and 2018, however, the distribution is indistinguishable from the one in Panel A (p-value of the Kolmogorov-Smirnov test = 0.113). Panel C shows the distribution of daily rainfall on the days where all other blood drives took place that are not part of the field

Figure 4: Distribution of daily rainfall in the greater Zurich region



Notes: Incidence and daily amounts in mm of rainfall in the greater Zurich region where all the blood drives take place. Panel A shows daily measures between the years 2000 and 2018, while Panel B and C focus on the days of the blood drives in the field experiment and the days of all other blood drives, respectively.

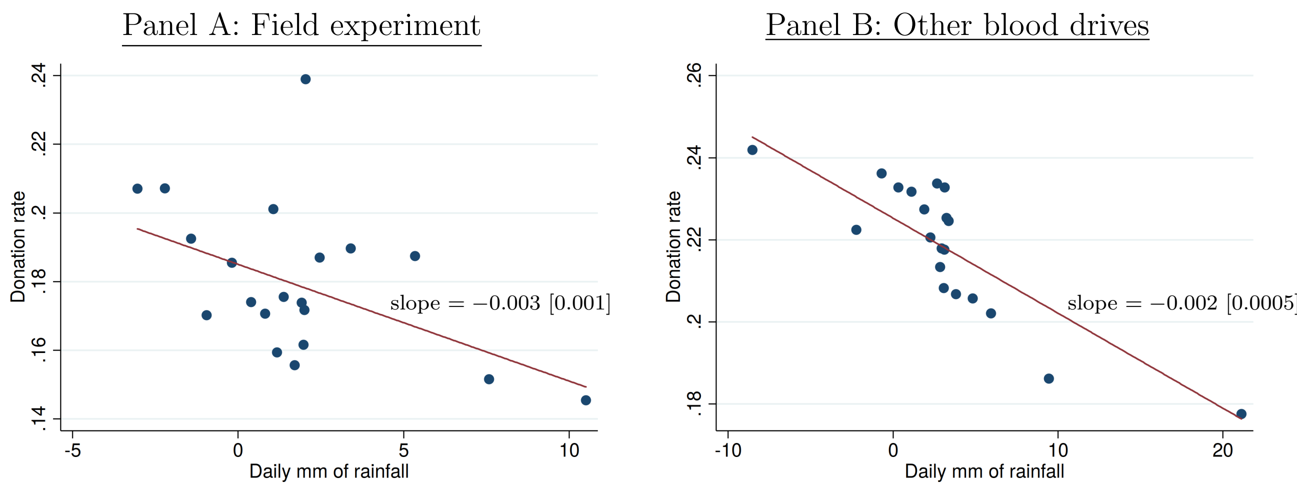
experiment. Again, the distribution is indistinguishable from the one in Panel A (p-value of the Kolmogorov-Smirnov test = 0.816).

3.3.2 Rainfall and Donation Rate

Figure 5 plots the effect of daily rainfall on the donation rate. Panel A focuses on blood drives where the field experiment took place, while Panel B focuses on all other blood drives. Two observations are noteworthy. First, daily rainfall has a negative effect on the donation rate. Second, the effect is non-linear, as light rainfall has only little impact on the donation rate, while strong rainfall leads to a substantial decline.

Since the effect of rainfall on the donation rate is non-linear, we construct an indicator for strong rainfall which will serve us as the second instrument to isolate the effect of habit formation. We define the threshold for strong rainfall in line with meteorological conventions as the 90th percentile of the rainfall distribution, corresponding to a daily amount of precipitation in excess of 10mm (see, for instance, Nelson et al. 2016).[8]

Figure 5: Effect of daily rainfall on the donation rate



Notes: Donation rate of invited donors as a function of rainfall on the day of the blood drives. Panel A shows the data of the blood drives in the field experiment while Panel B shows the data of all other blood drives. Both graphs absorb sponsor and year fixed effects. Standard errors in brackets are clustered at the individual- and blood-drive-level.

4 Behavioral Persistence

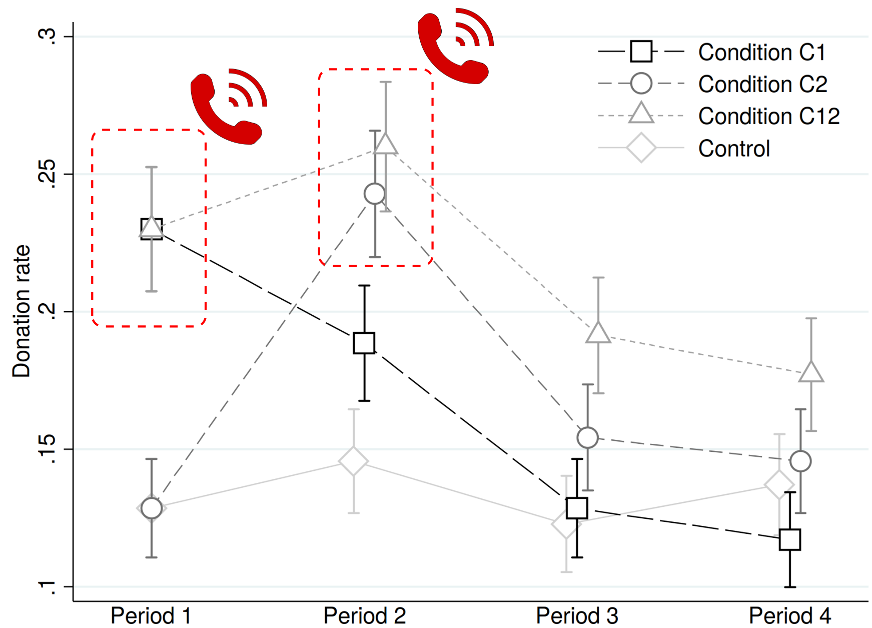
This section identifies behavioral persistence in blood donations using the randomized intervention of asking donors via phone to donate at the upcoming blood drive. We first show descriptive evidence. Subsequently, we introduce the econometric analysis and discuss the results.

4.1 Descriptive Evidence

Figure 6 exhibits descriptive evidence for behavioral persistence in blood donations. It shows how donation rates in the different experimental conditions evolved over the four periods of the field experiment. For now, we take an intention to treat (ITT) perspective and disregard whether donors answered the phone calls or not.

[8] Balance checks in Appendix Table B.2 confirm that the indicator for strong rainfall is orthogonal to the phone call during the first two periods where the phone call was administered.

Figure 6: Descriptive evidence for the persistent effects of the intervention



Notes: Donation rate as a function of the intervention over time. Red dashed frames indicate that the members of the corresponding condition receive the intervention in that period. Scatters show the means per condition, along with standard error bars.

Based on three observations we conclude that there is behavioral persistence in blood donations. First, we look at how the donation rate in condition C1 evolves. In period 1, donors in condition C1 receive a phone call asking them to donate at the upcoming blood drive. Their donation rate corresponds to roughly 23% in period 1, while their counterparts in the control condition and in condition C2 who are not called exhibit a donation rate of roughly 13%. Hence, asking for a donation directly increases the donation rate by roughly 10 percentage points. In period 2, the donation rate in condition C1 declines to about 18% but remains well above the one in the control condition. In fact, about half of the initial effect is still visible six months later – pointing towards behavioral persistence in blood donations. Only in period 3, the donation rate in condition C1 falls back to the level in the control condition.

Second, we look at the evolution of the donation rate in condition C2. In period 2, donors in condition C2 receive a phone call. Their donation rate immediately jumps by about 10 percentage points and, then, gradually declines over the following two periods.

Finally, we analyze how the donation rate in condition C12 evolves. Donors in condition C12 receive two phone calls, one in period 1 and one in period 2. Again, we find evidence for behavioral persistence. The donation rate of donors in condition C12 is about 10 percentage points above the one of their counterparts in the control condition during the two periods where they get a phone call and, then, gradually declines over the next two periods. Overall, the descriptive evidence indicates that there is behavioral persistence in blood donations, as the effect of asking donors by phone to donate at the upcoming blood drive lasts over several periods.

4.2 Econometric Analysis

We now turn to the econometric analysis which takes the panel structure of the data into account and features additional control variables. As in the descriptive analysis, we start by taking an ITT perspective. Subsequently, we focus on donors who answered the phone call and estimate the local average treatment effect (LATE) of asking donors to donate at the upcoming blood drive.

4.2.1 Setup

To obtain the ITT estimates, we estimate the following reduced-form specification:

$$\text{Donation}_{ib,t} = \beta_1 \text{Call}_{i,t} + \beta_2 \text{Call}_{i,t-1} + \beta_3 \text{Call}_{i,t-2} + \beta_4 \text{Call}_{i,t-3} + \phi' X_i + \delta_b + \epsilon_{ib,t}. \quad (4.1)$$

The binary outcome, $\text{Donation}_{ib,t}$, indicates whether donor i makes a donation at the upcoming blood drive b in the current period t. We include the indicator whether the donor receives a phone call, $\text{Call}_{i,t}$, in its contemporaneous form as well as with three lags. The vector X_i controls for the donor's individual characteristics gender, age, and blood type, while δ_b represents blood-drive-specific fixed effects. We control for individual characteristics to increase the precision of our estimates (see Athey and Imbens 2017). In an alternative specification, we replace the individual characteristics with individual-specific fixed effects.

Furthermore, to explore the role of multiple repeated phone calls, we estimate a version of the specification that features interactions between different lags of the phone call:

$$\text{Donation}_{ib,t} = \sum_{k=0}^{3} \beta_{k+1} \text{Call}_{i,t-k} + \sum_{k=0}^{2} \alpha_{k+1} \text{Call}_{i,t-k} \times \text{Call}_{i,t-k-1} + \delta_b + \nu_{ib,t}. \quad (4.2)$$

Finally, we estimate the LATE of asking donors to donate at the upcoming blood drive. That is, we estimate the analogue of Equation (4.1) by two-stage-least-squares (2SLS), using conducted phone calls as the instrument for answered phone calls. The first-stage-equations have the following form:

$$\text{Ask}_{ib,t-l} = \sum_{k=0}^{3} \iota_{k+1} \text{Call}_{i,t-l-k} + \phi' X_i + \delta_b + \epsilon_{ib,t-l}\,, \tag{4.3}$$

where $\text{Ask}_{ib,t-l}$ indicates whether donor i answered the phone call asking her to donate at the upcoming blood drive b in period $t-l$. $l \in \{0, 1, 2, 3\}$, as we need to estimate a separate first-stage-equation for the current period and each of the three lags. Based on the first-stage-estimates, we can predict whether the donor answers the phone and estimate the following second-stage-equation:

$$\text{Donation}_{ib,t} = \sum_{k=0}^{3} \omega_{k+1} \widehat{\text{Ask}_{ib,t-k}} + \phi' X_i + \delta_b + \epsilon_{ib,t}, \tag{4.4}$$

where $\widehat{\text{Ask}_{ib,t-k}}$ denotes the predicted values. In an alternative specification, we replace the individual characteristics, X_i, with individual-specific fixed effects. Finally, we obtain the LATE estimates for Equation (4.2) with interactions in an analogous manner.

Notice that whether we estimate the ITT or the LATE only changes the interpretation of the effect of the intervention on the donation rate. It leaves the extent of behavioral persistence in blood donations unchanged. This is because the extend of behavioral persistence in blood donations depends on the ratio between the lagged and the current intervention. Thus, defining the intervention as whether a phone call is attempted or whether a phone call is answered does not change this ratio.

4.2.2 Results

Table 3 reports the ITT estimates for the effects of the phone call on the donation rate. Column (1) shows the estimated coefficients of the specification in Equation (4.1) with individual characteristics and blood-drive-specific fixed effects. Column (2) shows the coefficients of the alternative specification that replaces the individual characteristics with individual-specific fixed effects. Column (3) displays the coefficients of the specification in Equation (4.2) with interactions between the different lags of the phone call.

There is evidence for behavioral persistence in blood donations in all three specifications. The phone call not only directly increases the donation rate by 9 to 14 percentage points, but also has significant lagged effects: a phone call one period or six months ago increases the current donation rate by 4 to 9 percentage points, while a phone call two periods or twelve months ago still leads to an increase by 3 to 6 percentage points. Only after three periods, the lagged effects become insignificant. Thus, the estimated coefficients indicate that the effect of the phone call decays over time but – due to behavioral persistence – lasts for at least one year.

Moreover, there is no evidence for interactions between different lags of the phone call. The coefficients on the interactions in Column (3) are all insignificant both individually and jointly (p=0.35). Thus, the effect of a phone call does not depend on the phone call in the previous period.

Table 4 displays the analogous estimates for the LATE of asking donors to donate at the upcoming blood drive.[9] The estimates reveal that asking donors to make a donation at the upcoming blood drive directly increases the donation rate in the current period by 18 to 26 percentage points, depending on the specification. There are also substantial lagged effects: Asking donors one period or six months ago increases the current donation rate by 8 to 17 percentage points, while asking them two periods or twelve months ago leads to an increase by 5 to 13 percentage points. In line with the estimates based on the ITT perspective, the lagged effects after eighteen months and the interactions between the different lags are insignificant. Taken together, the econometric analysis confirms that there is behavioral persistence in blood donations, causing the initial effect of an intervention on the donation rate to linger for at least one year.

[9]Table A.1 in the Appendix reports the first stages for asking, showing that only roughly half of the phone calls (53% in Column (1)) are answered. Consequently, the LATE estimates are roughly twice the magnitude of those based on the ITT perspective.

Table 3: ITT Results

Dependent variable: Donation$_t$	(1)	(2)	(3)
Call$_t$	0.0925***	0.125***	0.139***
	(0.0159)	(0.0230)	(0.0248)
Call$_{t-1}$	0.0385***	0.0710***	0.0896***
	(0.0139)	(0.0226)	(0.0277)
Call$_{t-2}$	0.0275**	0.0600***	0.0634**
	(0.0129)	(0.0213)	(0.0283)
Call$_{t-3}$	0.00373	0.0402	0.0376
	(0.0205)	(0.0313)	(0.0429)
Call$_t$ × Call$_{t-1}$			-0.0571
			(0.0368)
Call$_{t-1}$ × Call$_{t-2}$			-0.0184
			(0.0374)
Call$_{t-2}$ × Call$_{t-3}$			0.00381
			(0.0420)
Control mean	0.13	0.13	0.13
Joint F-tests:			
All lagged Calls=0	0.0182	0.00890	0.00466
All interactions=0			0.349
Individual controls	Y		
Blood drive FE	Y	Y	Y
Individual FE		Y	Y
Observations	5,600	5,600	5,600

Notes: In Column (1) the coefficients on the individual characteristics gender, age, and blood type are not shown. Standard errors clustered at the individual and blood drive level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: LATE Results

Dependent variable: Donation$_t$	(1)	(2)	(3)
Ask$_t$	0.175***	0.246***	0.263***
	(0.0295)	(0.0451)	(0.0489)
Ask$_{t-1}$	0.0767***	0.149***	0.171***
	(0.0268)	(0.0447)	(0.0552)
Ask$_{t-2}$	0.0535**	0.126***	0.125**
	(0.0244)	(0.0426)	(0.0565)
Ask$_{t-3}$	0.00861	0.0942	0.0843
	(0.0361)	(0.0595)	(0.0805)
Ask$_t$ × Ask$_{t-1}$			-0.126
			(0.122)
Ask$_{t-1}$ × Ask$_{t-2}$			-0.0219
			(0.122)
Ask$_{t-2}$ × Ask$_{t-3}$			0.0299
			(0.134)
Control mean	0.13	0.13	0.13
Joint F-tests:			
All lagged Asks=0	0.0165	0.00576	0.00807
All interactions=0			0.603
1^{st} stage instruments	155.7	123.8	28.13
Individual controls	Y		
Blood drive FE	Y	Y	Y
Individual FE		Y	Y
Observations	5,600	5,600	5,600

Notes: In Column (1) the coefficients on the individual characteristics gender, age, and blood type are not shown. Standard errors clustered at the individual and blood drive level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The LATE coefficients are obtained from 2SLS regressions using conducted phone calls as instruments for asking for donations.

5 Mechanisms Behind Behavioral Persistence

In this section, we discriminate between the two potential mechanisms behind the behavioral persistence in blood donations: habit formation and persistent changes in the donors' future motivation. We first present the identification strategy and its implementation. Subsequently, we discuss the results. Finally, we replicate the results in a larger quasi-experimental sample with a similar intervention. Since the discussion in this section relates to the validity of our instruments, we take the ITT perspective.

5.1 Identification Strategy

5.1.1 Identification Challenge

It is impossible to discriminate between the two mechanisms by relying exclusively on the intervention delivered by the phone call. On the one hand, the intervention may induce habit formation. However, on the other hand, it may also persistently change the donors' future motivation. Even though the phone calls in our setup do not explicitly stress the social benefits of donating, we cannot rule out that receiving them may have a persistent impact on donor motivation. More formally, reconsider the probability to donate at the upcoming blood drive, as shown in Equation (2.4) of our theoretical framework:

$$Pr(d_t = 1) = Pr(\tilde{c}_t \leq \gamma d_{t-1} + B) = F_c(\gamma d_{t-1} + B)\,.$$

Suppose that we aim to identify the habit formation parameter γ by using the phone call in period $t-1$ as an instrument for the donation in that period, d_{t-1}. Any persistent change the intervention may induce in the donors motivation B would be in the error term and, thus, would cause a violation of the exclusion restriction.

5.1.2 Second Instrument and Overidentification Test

To detect such a potential violation of the exclusion restriction, we require a second instrument for d_{t-1} which is both strong and valid. That is, the second instrument needs to affect the donors' probability to donate in a given period but leave their future motivation unchanged. Moreover, it should be at most only partially correlated with the phone call.

We use the indicator for strong rainfall as our second instrument, as it satisfies all aforementioned conditions. First, as we already showed in Section 3.3.2, strong rainfall has a negative effect on the donation rate, as it causes a temporary shock in the costs of donating $\tilde{c}_t$. Second, it is a valid instrument, as such a temporary shock in the costs of donating does not affect the donors' motivation six months later in the future.[10] Finally, the indicator for strong rainfall is orthogonal to the phone call, as the phone call is balanced within blood drives and, hence, daily weather conditions.

We rely on the second instrument to conduct an overidentification test – also referred to as *Sargan-Hansen J-test of Overidentifying Restrictions* (Sargan 1958; Hansen 1982) – and check whether the phone call satisfies the exclusion restriction. The test has the following intuition. If both instruments, the phone call and the indicator for strong rainfall, satisfy the exclusion restriction, the corresponding 2SLS-regression is valid and the residuals of the second stage are exogenous. However, if the phone call violates the exclusion restriction, e.g., it also affects the donors' future motivation, then the 2SLS-regression would be invalid and the residuals of the second stage would be correlated with at least one of the two instruments.

The null hypothesis of the overidentification test is that all instruments are exogenous to these residuals (Stock and Watson 2015). It constructs the residuals using the coefficients estimated from the second stage and regresses them on both instruments to test whether the null of a joint zero effect can be rejected. If the null hypothesis is not rejected, we conclude that the behavioral persistence in blood donations is exclusively driven by habit formation, and that the intervention of asking donors to make a donation at the upcoming blood drive has no direct effect on their future motivation.

To implement the overidentification test, we first estimate the following instrumental variables regression with 2SLS. The first stage has the following form:

$$\begin{aligned}\text{Donation}_{is,t-1} = \gamma_1 \text{Call}_{is,t-1} + \gamma_2 \text{Rainfall}_{s,t-1} + \gamma_3 \text{Call}_{is,t} + \gamma_4 \text{Rainfall}_{s,t} \\ + \gamma_5 X_i + \delta_w + \xi_{is,t-1}. \quad (5.1)\end{aligned}$$

The dependent variable, $\text{Donation}_{is,t-1}$, is the indicator whether donor i donated at the blood drive of sponsor s in period $t-1$. The independent variables comprise the two instruments, i.e., the indicators for the phone call, $\text{Call}_{is,t-1}$, and for strong rainfall on the day of the blood drive, $\text{Rainfall}_{is,t-1}$. We also include the future values of the instruments, $\text{Call}_{is,t}$ and $\text{Rainfall}_{is,t}$, since they will appear in the second stage. Moreover, we also control for the donor's individual characteristics, X_i, and fixed effects for the week of the year, δ_w.

[10]This condition would be violated if donors learn from current rainfall to anticipate future rainfall at the day of the next blood drive, which takes place 6 months in the future. While this is concern seems unjustified given the Swiss climate with frequent rainfall year-round, we look at inter-temporal correlations in rainfall events in Table B.1 in the Appendix. We link rainfall events for dates that are six months apart during the time of our field experiment as well as for the years 2000-2018 and find no significant correlations. Thus, we rule out this concern and conclude that the exclusion restriction holds for the rainfall instrument.

The second stage has the following form:

$$\text{Donation}_{is,t} \;=\; \mu_1 \widehat{\text{Donation}_{is,t-1}} \;+\; \mu_2 \text{Call}_{is,t} \;+\; \mu_3 \text{Rainfall}_{s,t} \;+\; \mu_4 X_i \;+\; \theta_w \;+\; \zeta_{is,t} \quad (5.2)$$

It regresses donations in period t on the predicted values $\widehat{\text{Donation}_{is,t-1}}$ from the first stage; the future values of the instruments, $\text{Call}_{is,t}$ and $\text{Rainfall}_{is,t}$; the individual characteristics; and the fixed effects for the week of the year.

After estimating the second stage, we regress its residuals, $\hat{\zeta}^{tsls}_{is,t}$, on the two instruments and all other exogenous variables:[11]

$$\hat{\zeta}^{tsls}_{is,t} = \lambda_1 \text{Call}_{is,t-1} + \lambda_2 \text{Rainfall}_{s,t-1} + \lambda_3 \text{Call}_{is,t} + \lambda_4 \text{Rainfall}_{s,t} + \lambda_5 X_i + \lambda_w + \epsilon_{is,t}. \quad (5.3)$$

Under the null hypothesis that both instruments are exogenous the test statistic of the joint F-test $\lambda_1 = \lambda_2 = 0$ is χ^2_1 distributed.[12]

5.2 Results

Table 5 displays the results. Columns (1) and (2) exhibit the first- and second-stage-estimates as well as the p-value of the overidentification test. In the first stage, both excluded instruments are strong, and the joint Kleibergen/Paap F-statistic on both instruments is 35.5 – well above the conventional thresholds for strong instruments. In the second stage, the estimated coefficient on the past donation is 0.4. Importantly, the p-value of the overidentification test is 0.795. Thus, we do not reject the null hypothesis that both instruments are valid.

The conclusion from the overidentification test can also be illustrated by varying the instruments we use. In Columns (3) and (4), we show the second stage estimates when we include only one instrument at a time in the first stage – the indicator for the phone call in Column (3) and the indicator for strong rainfall in Column (4). If the phone call violated the exclusion restriction, the second stage coefficient on the effect of lagged donations in Column (3) would exhibit endogeneity bias and would differ from the coefficient in Column (4) which is based on the indicator for strong rainfall. However, the coefficients on the effect of lagged donations are remarkably similar in Columns (3) and (4). Thus, we find no evidence for

[11]Residuals are based on coefficient estimates from the second stage, but the true regressors rather than predicted values from the first stage (see Stock and Watson 2015).

[12]The *p*-value of the overidentifying restrictions test reported in Table 5 relies on a cluster-robust version (see Hayashi 2000, pp. 227f).

endogeneity bias and confirm the result of the overidentification test that both instruments are valid.

Finally, we look at the test from yet another angle and perform the following additional check. If both instruments satisfy the exclusion restriction and only affect the future donation rate through an increase in contemporaneous donations, the instruments should not correlate with future donations once we control for that channel. Columns (5)-(6) show the results of the second stage when we include only one instrument at a time in the first stage but *include the other instrument as a control variable* in the second stage. In line with the result of the overidentification test, neither the indicator for the lagged phone call nor the indicator for strong rainfall have a direct effect on current donations once we control for predicted past donations.

Taken together, these results indicate that the phone call has no direct effect on the donors' future motivation and that the behavioral persistence in blood donations is due to habit formation.

Table 5: Habit formation vs persistent increases in the donors' motivation

	(1)	(2)	(3)	(4)	(5)	(6)
	1^{st} stage			2^{nd} stages		
Dependent variable:	Donation_{t-1}	Donation_t	Donation_t	Donation_t	Donation_t	Donation_t
$\widehat{\text{Donation}_{t-1}}$		0.409***	0.403***	0.482*	0.400***	0.508
		(0.122)	(0.131)	(0.275)	(0.135)	(0.364)
Call_{t-1}	0.0944***					-0.0102
	(0.0147)					(0.0393)
Rainfall_{t-1}	-0.0664***				-0.00714	
	(0.0168)				(0.0270)	
Call_t	-0.0252	0.0944***	0.0944***	0.0939***	0.0939***	0.0966***
	(0.0163)	(0.0174)	(0.0174)	(0.0178)	(0.0175)	(0.0199)
Rainfall_t	0.0179	-0.0397	-0.0396	-0.0407	-0.0396	-0.0415
	(0.0233)	(0.0289)	(0.0287)	(0.0302)	(0.0287)	(0.0308)
Instrument in the 1^{st} stage		Both	Call	Rainfall	Call	Rainfall
Kleibergen/Paap F-statistic	35.50		43.64	19.99	41.13	15.64
Sargan-Hansen J-test (p-val.)		0.795				
Observations	4,200	4,200	4,200	4,200	4,200	4,200

Notes: Regressions additionally include individual controls (gender, age, blood type) and week of the year fixed effects. Standard errors clustered at the individual and blood drive level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.3 Replication

As a robustness check, we conduct a replication study in a larger quasi-experimental sample featuring a similar intervention. The quasi-experiment took place in the greater Zurich region between 2012 and 2014.

The intervention is also delivered by a phone call. However, the phone call conveys a shortage message and is randomized conditional on blood types. That is, depending on the daily inventory in its blood stock, the BTSRC determines which blood types are in short supply and calls a random subset of invited donors with the required blood types. In the phone call, the BTSRC's staff tells donors that their blood type is in short supply and encourages them to donate at the upcoming blood drive. The message of the phone call differs from the one in field experiment in the sense that it points out the temporary shortage in the donors' blood types and does not ask them for a commitment. Moreover, in this quasi-experiment, only 14% of the invited donors ever receive a phone call and most of them get called only once.[13]

Even though the quasi-experiment has less power to identify habit formation, we find qualitatively identical results and, again, do not reject the null hypothesis that both instruments are valid (p=0.3). Appendix C presents the results in detail.

6 Structural Estimation of the Habit Formation Parameter

After having confirmed that the mechanism behind the behavioral persistence in blood donations is habit formation, we now estimate the habit formation parameter structurally. First, we use the theoretical framework from Section 2 to identify the contemporaneous and lagged effects of the intervention of asking donors by phone to donate at the upcoming blood drive on their probability to donate. Subsequently, we impose the resulting structure on our linear probability model to estimate the habit formation parameter γ and discuss the results. To be in line with the theoretical framework, we present this section in terms of the LATE.[14]

[13] We make the sample as comparable as possible to our field experiment by focusing on inactive donors who have not donated in the past year and have the same blood types O-, O+, and A-, as well as by limiting the data set to sponsors with blood drives scheduled regularly every 6 months.

[14] In Appendix D we alternatively take the ITT perspective to estimate the habit formation parameter. The results are virtually identical.

6.1 Theoretical Framework

We can use the structure of the theoretical framework in Section 2 to trace out the contemporaneous and lagged effects of the intervention on the probability to donate. Assume that asking donors to donate increases their motivation by η in the current period. Because the intervention is randomized, all other factors influencing the motivation to donate are the same. Moreover, all donors in our sample have not donated for at least a year prior to the study. Thus, $S_1 = 0$ in all experimental conditions. Consequently, donors in the treatment conditions will donate with probability $p_t^T = F_c(B + \eta)$, while those in the control condition will donate with probability $p_t^C = F_c(B)$.[15] The difference between the two is the treatment effect of the intervention,

$$\Delta p_t = F_c(B + \eta) - F_c(B)\,. \tag{6.1}$$

In period $t + 1$, the impact of the intervention in period t continues to affect the behavior of donors in the treatment conditions through habit formation. Hence, their probability to donate is $p_{t+1}^T = p_t^T F_c(B+\gamma) + (1-p_t^T)F_c(B) = F_c(B+\eta)F(B+\gamma) + (1-F_c(B+\eta))F_c(B)$, whereas the probability to donate of their counterparts in the control condition is $p_{t+1}^C = p_t^C F_c(B+\gamma) + (1-p_t^C)F_c(B) = F_c(B)F(B+\gamma) + (1-F_c(B))F_c(B+\gamma)$. Again, the difference between the two corresponds to the treatment effect,

$$\Delta p_{t+1} = \Delta p_t(F_c(B + \gamma) - F_c(B))\,.$$

Iterating forward, we see a geometric sequence emerging: in period $t + 2$, the impact of the intervention from period t continues to affect the behavior of donors in the treatment conditions through habit formation. Their probability to donate is $p_{t+2}^T = p_{t+1}^T F_c(B + \gamma) + (1 - p_{t+1}^T)F_c(B)$, while the probability to donate of the donors in the control condition is $p_{t+2}^C = p_{t+1}^C F_c(B + \gamma) + (1 - p_{t+1}^C)F_c(B)$. Thus, the treatment effect is

$$\Delta p_{t+2} = \Delta p_{t+1}(F_c(B + \gamma) - F_c(B)) = \Delta p_t(F_c(B + \gamma) - F_c(B))^2\,.$$

Generally, the treatment effect in period $t + k$ is

$$\Delta p_{t+k} = \Delta p_t(F_c(B + \gamma) - F_c(B))^k. \tag{6.2}$$

[15] We abstract from other motivations for prosocial behavior, such as peer effects (Goette and Tripodi forthcoming). Bruhin et al. (2020) find motivational spillovers between blood donors. However, we formally show in Appendix E that such motivational spillovers do not affect the estimates of persistence to a first approximation.

Thus, the intervention's lagged treatment effects in Equation (6.2) follow a geometric sequence proportional to the impact of the contemporaneous effect in Equation (6.1).

6.2 Estimation

To estimate the habit formation parameter, we impose the above structure on our linear probability model:

$$\text{Donation}_{ib,t} = \beta_1(\text{Ask}_{i,t} + \gamma_1\text{Ask}_{i,t-1} + \gamma_1^2\text{Ask}_{i,t-2} + \gamma_1^3\text{Ask}_{i,t-3}) + \beta_2' X_i + \delta_b + \epsilon_{ib,t}\,, \quad (6.3)$$

where $\beta_1 = F_c(B+\eta) - F_c(B)$, and $\gamma_1 = F_c(B+\gamma) - F_c(B)$.[16] If the costs, $\tilde{c}_t$, follow a uniform distribution, β_1 and γ_1 are structural parameters of our framework, normalized by a constant. If the costs follow a general distribution, the same holds approximately by the mean value theorem. However, note that departures from uniformity would imply that the effect of the intervention in a given period depends on the intervention in the previous period, for which we found no evidence in Table 3 (Column (3)). Thus, we focus on the uniform case and ignore these higher-order terms in our estimation below. Furthermore, we treat the control variables and fixed effects as outside the structure.

Since γ_1 enters Equation (6.3) non-linearly, we search over a grid of γ in the range of [0.1,0.9] in steps of 0.01. The optimal γ^* in terms of minimizing the residual sum of squares feeds into the second step, where we estimate the same regression model for a grid of γ in the range of $[\gamma^* - 0.01, \gamma^* + 0.01]$ in steps of 0.001 to obtain a more precise estimate γ^{**}. Due to this procedure, we need to bootstrap the standard errors, while maintaining the clustering at the sponsor and individual level from the earlier specifications.

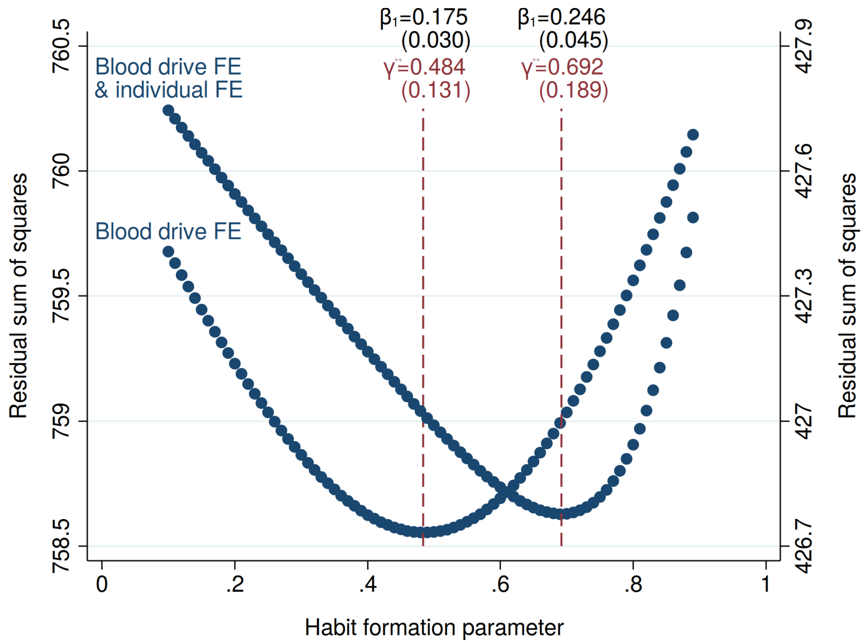
Compared to estimating the habit formation parameter in the IV model, this approach is more efficient, because it exploits the implications of the structural model for higher lags of the intervention.

6.3 Results

Figure 7 shows the residual sum of squares for different values of the habit formation parameter γ. One specification corresponds to Equation (6.3) that controls for individual characteristics and blood drive fixed effects. The other, alternative specification is more general and replaces the individual characteristics with individual fixed effects. For both specifications, the residual sum of squares exhibits a unique minimum. Thus, γ is well-identified in both specifications.

[16] As before, we can obtain the LATE using 2SLS.

Figure 7: Grid search of the habit formation parameter



Notes: Relationship between γ and the residual sum of squares. Optimal γ^{**} is chosen to minimize the residual sum of squares. Two-way individual and blood drive cluster robust standard standard errors from 1,000 bootstrap replications in parentheses.

The estimates of the habit formation parameter, γ^{**}, are 0.484 ($p < 0.01$) and 0.692 ($p < 0.01$), respectively.[17] Hence, we reject the null hypothesis of no habit formation. Both estimates are also significantly smaller than 1 ($p < 0.01$ and $p = 0.05$, respectively), allowing us to also reject a model in which habit formation leads to a permanent change in behavior. Quantitatively, the estimates imply that donating at a blood drive today increases the probability of donating at the consecutive blood drive of the same sponsor six months later by 48 or 69 percentage points.

To put the effect of habit formation into perspective, we compare it to the direct effect of the intervention. The estimates indicate that the effect of donating today on the probability of donating at the consecutive blood drive is almost three times larger than the direct effect of asking donors by phone to make a donation.

Due to this amplification of the direct effect of a policy intervention, habit formation has a substantial economic impact. Consider our example of calling donors and asking them to donate at the upcoming blood drive. If we use the more conservative estimates from Table 4 and γ, the direct effect of the successful phone calls on the donation rate is 18 percentage points. However, according to the geometric series in Equation (6.2), habit formation leads

[17]The estimated γ reflects habit formation net of time discounting, as we do not separately estimate the discount rate.

to a multiplier that amplifies the direct effect by $1/(1-\gamma)$. Thus, with our estimate of γ equal 0.484 habit formation amplifies the effect of successful phone call to a total of 34 percentage points – making the intervention almost twice as effective. In other words, to get one additional donation, the BTSRC would have to reach 1/0.18 or roughly six donors by phone without habit formation. However, with habit formation, it only needs to reach three donors.

7 Conclusion

In this paper, we discriminate between two potential mechanisms behind the behavioral persistence in voluntary blood donations – habit formation and persistent changes in the donor's motivation. We combine a field experiment, asking a random subset of inactive blood donors to donate, with a natural experiment, exploiting random fluctuations in rainfall on the days of blood drives. This combination of two experiments allows us to demonstrate that the behavioral persistence in voluntary blood donations is driven by habit formation.

Identifying habit formation as the underlying mechanism is relevant not only for welfare analysis but also for the design of effective policy interventions in the future. Since behavioral persistence is driven by habit formation, any policy intervention triggering an initial engagement in the prosocial activity benefits from a multiplier, as individuals form a habit and continue to engage in the prosocial activity even after the intervention ended. If policy makers aim to maximize the long-run impact of an intervention, our results suggest that they should choose the intervention with the strongest immediate impact. In contrast, if behavioral persistence were driven by changes in motivation, the long-term effect of a policy intervention would depend on its ability to persistently change the individuals' future motivation. In that case, policy makers would require detailed understanding of how different interventions affect future motivation.

Our results are also in contrast to studies on charitable donations, which often find evidence that asking for donations can lower future donations due to ask avoidance (Damgaard and Gravert 2018; Adena and Huck 2020; Andreoni, Rao and Trachtman 2017; DellaVigna, List and Malmendier 2012). A possible explanation for the contrast between our findings and these studies is that blood donors have more trust in the BTSRC than charitable donors in charities. While charitable donations can easily be misappropriated for other purposes, blood donations have a clear purpose of use as they can only be used for blood transfusion and medical research. Asking individuals for monetary donations may also activate overhead aversion (Gneezy, Keenan and Gneezy 2014), as the infrastructure necessary to reach out to donors to solicit them may serve as an unwitting reminder of the organization's overhead, to which part of the donation will necessarily contribute to. In contrast, blood donors do not have this concern as they contribute exclusively to the final use of their transfusion and never to the coverage of overhead costs. Last but not least, there may be unobserved substitution effects in charitable donations: due to the plethora of charities, donors may substitute their donations at one charity with donations at another, potentially unobserved charity. In contrast, blood donors only have one option where they can donate their blood – the BTSRC. This underlines the importance of studying the prosocial behavior in the context of non-pecuniary donations.

Our results also raise questions for future research. We show that current donations increase the probability of future donations consistent with the habit-forming mechanism in Stigler and Becker (1977). However, it is not clear which aspect of the behavior is habit forming: is it the narrowly-defined act of donating blood, or is it a potentially broader warm glow from prosocial behavior that exhibits a complementarity between current and future donation? While narrowly-defined habit formation with regard to one behavior already has important policy implications for the specific prosocial behavior under study, discovery of a broader “moral habit capital” could have more sweeping implications: one charity’s work would impact the future willingness of its donors to engage in a wide array of prosocial behaviors. Future research should thus study whether and how interventions on one type of prosocial behavior spill over to other behaviors in subsequent periods.

References

Acland, Dan and Matthew R Levy. 2015. "Naiveté, projection bias, and habit formation in gym attendance." *Management Science* 61(1):146–160.

Adena, Maja and Steffen Huck. 2019. "Giving once, giving twice: A two-period field experiment on intertemporal crowding in charitable giving." *Journal of Public Economics* (172):127–134.

Adena, Maja and Steffen Huck. 2020. "Online fundraising, self-image, and the long-term impact of ask avoidance." *Management Science* 66(2):722–743.

Allcott, Hunt and Todd Rogers. 2014. "The Short-Run and Long-Run Effects of Behavioral Interventions: Experimental Evidence from Energy Conservation." *American Economic Review* 104:3003–3037.

Andreoni, James and Justin M Rao. 2011. "The power of asking: How communication affects selfishness, empathy, and altruism." *Journal of Public Economics* 95(7-8):513–520.

Andreoni, James, Justin M Rao and Hannah Trachtman. 2017. "Avoiding the ask: A field experiment on altruism, empathy, and charitable giving." *Journal of Political Economy* 125(3):625–653.

Aronsson, Thomas and Karl-Gustaf Löfgren. 2008. "Welfare equivalent NNP and habit formation." *Economics Letters* 98:84–88.

Athey, Susan and Guido W Imbens. 2017. The econometrics of randomized experiments. In *Handbook of Economic Field Experiments*. Vol. 1 Elsevier pp. 73–140.

Benartzi, Shlomo, John Beshears, Katherine L Milkman, Cass R Sunstein, Richard H Thaler, Maya Shankar, Will Tucker-Ray, William J Congdon and Steven Galing. 2017. "Should governments invest more in nudging?" *Psychological Science* 28(8):1041–1055.

Brückner, Markus and Antonio Ciccone. 2011. "Rain and the democratic window of opportunity." *Econometrica* 79(3):923–947.

Bruhin, Adrian, Lorenz Goette, Adrian Roethlisberger, Alexander Markovic, Regula Buchli and Beat M Frey. 2015. "Call of Duty: The Effects of Phone Calls on Blood Donor Motivation." *Transfusion* 55(11):2645–2652.

Bruhin, Adrian, Lorenz Goette, Simon Haenni and Lingqing Jiang. 2020. "Spillovers of prosocial motivation: Evidence from an intervention study on blood donors." *Journal of Health Economics* 70:102244.

Byrne, David P., Lorenz Goette, Leslie A. Martin, Lucy Delahey, Alana Jones, Amy Miles, Samuel Schob, Thorsten Staake and Verena Tiefenbeck. 2019. "The habit-forming effects of feedback: evidence from a large-scale Field experiment." WP.

Camerer, Colin F., Peter Landry and Ryan Webb. 2020. The Neuroeconomics of Habit. In *The State of Mind in Economics*, ed. Alan Kirman and M. Tedeschi. Oxford: Oxford University Press. forthcoming.

Carrasco, R., J. Labeaga and J. D. Lopez-Salido. 2005. "Consumption and Habits: Evidence from Panel Data." *Economic Journal* 115:144–165.

Charness, Gary and Uri Gneezy. 2009. "Incentives to Exercise." *Econometrica* 77:909–931.

Cialdini, Robert B and Melanie R Trost. 1998. "Social influence: Social norms, conformity and compliance.".

Cialdini, Robert B, Melanie R Trost and Jason T Newsom. 1995. "Preference for consistency: The development of a valid measure and the discovery of surprising behavioral implications." *Journal of Personality and Social Psychology* 69(2):318.

Cialdini, Robert B and Noah J Goldstein. 2004. "Social influence: Compliance and conformity." *Annu. Rev. Psychol.* 55:591–621.

Damgaard, Mette Trier and Christina Gravert. 2018. "The hidden costs of nudging: Experimental evidence from reminders in fundraising." *Journal of Public Economics* 157:15–26.

DellaVigna, Stefano, John A List and Ulrike Malmendier. 2012. "Testing for altruism and social pressure in charitable giving." *Quarterly Journal of Economics* 127(1):1–56.

Freedman, Jonathan L and Scott C Fraser. 1966. "Compliance without pressure: the foot-in-the-door technique." *Journal of Personality and Social Psychology* 4(2):195.

Freeman, Richard B. 1997. "Working for nothing: The supply of volunteer labor." *Journal of Labor Economics* 15(1, Part 2):S140–S166.

Fuhrer, Jeffrey C. 2000. "Habit Formation in Consumption and Its Implications for Monetary-Policy Models." *American Economic Review* 90:367–390.

Fujiwara, Thomas, Kyle Meng and Tom Vogl. 2016. "Habit Formation in Voting: Evidence from Rainy Elections." *American Economic Journal: Applied Economics* 8:160–188.

Gerber, Alan S, Donald P Green and Ron Shachar. 2003. "Voting may be habit-forming: evidence from a randomized field experiment." *American Journal of Political Science* 47(3):540–550.

Gneezy, Ayelet, Alex Imas, Amber Brown, Leif D Nelson and Michael I Norton. 2012. "Paying to be nice: Consistency and costly prosocial behavior." *Management Science* 58(1):179–187.

Gneezy, Uri, Elizabeth A Keenan and Ayelet Gneezy. 2014. "Avoiding overhead aversion in charity." *Science* 346(6209):632–635.

Goette, Lorenz and Alois Stutzer. 2020. "Blood donations and incentives: Evidence from a field experiment." *Journal of Economic Behavior and Organization* 170:52–74.

Goette, Lorenz, Alois Stutzer, Gürcan Yavuzcan and Beat M. Freydur. 2009. "Free Cholesterol Testing as A Motivation Device in Blood Donations: Evidence from Field Experiments." *Transfusion* 49(March):524–531.

Goette, Lorenz and Egon Tripodi. forthcoming. "Social Influence in Prosocial Behavior: Evidence from a Large-Scale Experiment." *Journal of the European Economic Association* .

Hansen, Lars Peter. 1982. "Large sample properties of generalized method of moments estimators." *Econometrica: Journal of the Econometric Society* pp. 1029–1054.

Hayashi, Fumio. 2000. *Econometrics*. Princeton University Press.

Hussam, Reshmaan, Atonu Rabbani, Giovanni Reggiani and Natalia Rigol. 2022. "Rational Habit Formation: Experimental Evidence from Handwashing in India." *American Economic Journal: Applied Economics* 14(1):1–41.

Lacetera, Nicola, Mario Macis and Robert Slonim. 2012a. "Will There Be Blood? Incentives and Displacement Effects in Pro-Social Behabior." *American Economic Journal* 4(1):186–223.

Lacetera, Nicola, Mario Macis and Robert Slonim. 2013. "Economic Rewards to Motivate Blood Donations." *Science* 340(6135):927–928.

Lacetera, Nicola, Mario Macis and Robert Slonim. 2014. "Rewarding volunteers: a field experiment." *Management Science* 60(5):1107–1129.

Landry, Craig E, Andreas Lange, John A List, Michael K Price and Nicholas G Rupp. 2006. "Toward an understanding of the economics of charity: Evidence from a field experiment." *Quarterly Journal of Economics* 121(2):747–782.

Landry, Craig E., Andreas Lange, John A. List, Michael K. Price and Nicholas G. Rupp.

2010. "Is a Donor in Hand Better than Two in the Bush? Evidence from a Natural Field Experiment." *American Economic Review* 100:958–983.

Loewenstein, George, Joseph Price and Kevin Volpp. 2016. "Habit formation in children: Evidence from incentives for healthy eating." *Journal of Health Economics* 45:47–54.

Maccini, Sharon and Dean Yang. 2009. "Under the weather: Health, schooling, and economic consequences of early-life rainfall." *American Economic Review* 99(3):1006–26.

Meer, Jonathan. 2013. "The habit of giving." *Economic Inquiry* 51(4):2002–2017.

Meier, Stephan. 2007. "Do Subsidies Increase Charitable Giving in the Long Run? Matching Donations in a Field Experiment." *Journal of the European Economic Association* 5:1203–1222.

Merritt, Anna C, Daniel A Effron and Benoît Monin. 2010. "Moral self-licensing: When being good frees us to be bad." *Social and Personality Psychology Compass* 4(5):344–357.

Miguel, Edward, Shanker Satyanath and Ernest Sergenti. 2004. "Economic shocks and civil conflict: An instrumental variables approach." *Journal of Political Economy* 112(4):725–753.

Milkman, Katherine L, John Beshears, James J Choi, David Laibson and Brigitte C Madrian. 2011. "Using implementation intentions prompts to enhance influenza vaccination rates." *Proceedings of the National Academy of Sciences* 108(26):10415–10420.

Milkman, Katherine L, John Beshears, James J Choi, David Laibson and Brigitte C Madrian. 2012. Following through on good intentions: The power of planning prompts. Technical report National Bureau of Economic Research.

Naik, N. Y. and M. J. Moore. 1996. "Habit formation and intertemporal substitution in individual food consumption." *Review of Economics and Statistics* 78:321–328.

Nelson, Brian R, Olivier P Prat, D-J Seo and Emad Habib. 2016. "Assessment and implications of NCEP Stage IV quantitative precipitation estimates for product intercomparisons." *Weather and Forecasting* 31(2):371–394.

Obama. 2015. "Executive order? Using behavioral science insights to better serve the American people." Retrieved from https://www.whitehouse.gov/the-press-office/2015/09/15/executive-order-using-behavioral-science-insights-better-serve-american.

Putnam, Robert D. 1995. "Tuning in, tuning out: The strange disappearance of social capital in America." *PS: Political Science & Politics* 28(4):664–683.

Sargan, John D. 1958. "The estimation of economic relationships using instrumental variables." *Econometrica: Journal of the Econometric Society* pp. 393–415.

Steiny Wellsjo, Alexandra. 2021. Simple Actions, Complex Habits: Lessons from Hospital Hand Hygiene. Working paper UC Berkeley.

Stigler, George J and Gary S Becker. 1977. "De gustibus non est disputandum." *American Economic Review* 67(2):76–90.

Stock, James H and Mark W Watson. 2015. *Introduction to Econometrics*.

Wood, W. and D. T. Neal. 2007. "A new look at habits and the habit-goal interface." *Psychological Review* 114:843.

Wood, Wendy and Dennis Rünger. 2016. "Psychology of habit." *Annual Review of Psychology* 67.

World Health Organization. 2011. "Global Database on Blood Safety." *Summary Report* .

Yang, Nan and Long Yong Lim. 2017. "Temporary Incentives Change Daily Routines: Evidence from a Field Experiment on Singapore's Subways." *Management Science* 64:3365–3379.

Appendix A First stages of LATE estimations

Table A.1: LATE First Stages

	Specification (1)				Specification (2)				Specification (3)						
Dependent variable	(1) Ask_t	(2) Ask_{t-1}	(3) Ask_{t-2}	(4) Ask_{t-3}	(5) Ask_t	(6) Ask_{t-1}	(7) Ask_{t-2}	(8) Ask_{t-3}	(9) Ask_t	(10) Ask_{t-1}	(11) Ask_{t-2}	(12) Ask_{t-3}	(13) $\text{Ask}_t \times \text{Ask}_{t-1}$	(14) $\text{Ask}_{t-1} \times \text{Ask}_{t-2}$	(15) $\text{Ask}_{t-2} \times \text{Ask}_{t-3}$
Call_t	0.530***	-0.00137	0.000457	0.000162	0.524***	-0.0118	-0.0142	-0.000608	0.546***	-0.0186	-0.0128	1.91e-05	0.000123	7.78e-05	0.000117
	(0.0195)	(0.00760)	(0.000409)	(0.000225)	(0.0211)	(0.0129)	(0.00879)	(0.00141)	(0.0189)	(0.0161)	(0.0151)	(0.00605)	(0.000194)	(0.000161)	(0.000153)
Call_{t-1}	-0.0121	0.530***	-0.00136	0.000166	-0.0183	0.519***	-0.0160	-0.000608	0.00757	0.529***	-0.0220	3.28e-05	3.53e-05	0.000248	0.000201
	(0.00984)	(0.0195)	(0.00760)	(0.000227)	(0.0171)	(0.0173)	(0.0127)	(0.00164)	(0.0128)	(0.0221)	(0.0172)	(0.00435)	(0.000183)	(0.000282)	(0.000216)
Call_{t-2}	0.000453	-0.0121	0.530***	-0.00166	-0.00574	-0.0225**	0.515***	-0.00243	-0.00215	-0.0108	0.528***	6.83e-05	-6.00e-05	0.000190	0.000418
	(0.000417)	(0.00984)	(0.0195)	(0.00763)	(0.0169)	(0.0107)	(0.0173)	(0.0110)	(0.0121)	(0.0137)	(0.0236)	(0.00272)	(0.000198)	(0.000237)	(0.000353)
Call_{t-3}	0.000505	0.000506	-0.0246	0.570***	-0.0151	-0.0200	-0.0534**	0.569***	-0.0154	-0.0297	-0.0135	0.574***	-7.07e-05	0.000165	0.000543
	(0.000633)	(0.000654)	(0.0196)	(0.0284)	(0.0211)	(0.0156)	(0.0226)	(0.0253)	(0.0181)	(0.0218)	(0.0183)	(0.0280)	(0.000298)	(0.000292)	(0.000533)
$\text{Call}_t \times \text{Call}_{t-1}$									-0.0886**	0.0223	0.0147	-2.19e-05	0.312***	-0.000165	-0.000134
									(0.0348)	(0.0295)	(0.0229)	(0.0118)	(0.0339)	(0.0152)	(0.0152)
$\text{Call}_{t-1} \times \text{Call}_{t-2}$									-0.0149	-0.0664**	0.0293	-5.46e-05	9.85e-05	0.312***	-0.000335
									(0.0309)	(0.0337)	(0.0327)	(0.0116)	(0.0152)	(0.0339)	(0.0152)
$\text{Call}_{t-2} \times \text{Call}_{t-3}$									0.000408	0.0146	-0.0599	-0.00746	0.000169	-0.000185	0.312***
									(0.0314)	(0.0232)	(0.0366)	(0.0280)	(0.0152)	(0.0152)	(0.0339)
Joint F-tests:															
1^{st} stage instruments		155.7				123.8							28.13		
Individual controls		Y													
Blood drive FE		Y				Y							Y		
Individual FE						Y							Y		
Observations		5,600				5,600							5,600		

Notes: First stages corresponding to Table 4. In Column (1-3) the coefficients on the individual characteristics gender, age, and blood type are not shown. Standard errors clustered at the individual and blood drive level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$..

Appendix B Checks on Rainfall Instrument

Table B.1: Correlation between Rainfall on Different Days

	(1)	(2)
Dependent variable:	Rainfall$_t$	Rainfall$_t$
Rainfall$_{t+180}$	-0.0317	0.00780
	(0.0295)	(0.0125)
Constant	0.0880***	0.0985***
	(0.0111)	(0.00382)
Years	2015-2016	2000-2018
Observations	730	6,760

Notes: Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Balance Checks of Covariates

	(1) No heavy rainfall	(2) Heavy rainfall	(3) Difference
Call	0.4996	0.5094	0.0098
	(0.5001)	(0.5023)	(0.0495)
Age	41.2736	43.5660	2.2925*
	(13.4996)	(13.8447)	(1.3380)
Male	0.5097	0.5566	0.0470
	(0.5000)	(0.4991)	(0.0495)
O+ blood type	0.8244	0.7830	-0.0414
	(0.3805)	(0.4141)	(0.0378)
O- blood type	0.0590	0.0849	0.0259
	(0.2357)	(0.2801)	(0.0235)
A- blood type	0.1166	0.1321	0.0155
	(0.3209)	(0.3402)	(0.0319)
Observations	2,694	106	2,800

Notes: Means with standard deviations in parentheses. Balance checks focus on the first two periods of the experiment, as the phone call was administered during these periods (see Table 1). The variable Call indicates the frequency of the phone call. Level of significance from two-sides t-test: * $p < 0.1$.

Appendix C Replication Study

Table C.1 shows the results, analogously to Table 5. In the first stage in Column (1), both excluded instruments are strong with a joint F-statistic of 27. Compared to Table 5, the coefficients on the excluded instruments are within the confidence bounds. The estimated second stage coefficient on the past donation in Column (2) is 0.26. The p-value of the Sargan-Hansen J-test of overidentifying restrictions is 0.3, indicating that the null hypothesis that both instruments are exogenous is not rejected.

Columns (3)-(4) show the second stage estimates when excluding only one instrument at a time. Consistent with the insignificant overidentifying restrictions test the estimated effect of past donation is within the confidence bounds in both columns and both instruments are individually strong. The coefficient on past donation is even somewhat *smaller* when using the phone call compared to using rainfall as instrument - the opposite as would be expected if the phone call had persistent effects on the motivation to donate.

Columns (5)-(6) exclude only one instrument at a time, while *including the additional instrument* as control variable. As expected, neither the lagged phone call, nor the lagged rainfall have a persistent direct effect on donations, once controlling for past donations.

Even tough the quasi-experimental data is not directly comparable to the field experiment and is considerably more noisy, qualitatively the results from this replication exercise are reassuringly consistent.

Table C.1: Habit formation vs lagged effects (replication study)

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Donation_{t-1}	Donation_{t}	Donation_{t}	Donation_{t}	Donation_{t}	Donation_{t}
$\widehat{\text{Donation}_{t-1}}$		0.255*	0.221	0.529*	0.217	0.561*
		(0.140)	(0.155)	(0.292)	(0.157)	(0.330)
Phone call_{t-1}	0.120***					-0.0414
	(0.0178)					(0.0460)
Rainfall_{t-1}	-0.0980***				-0.0337	
	(0.0302)				(0.0312)	
Phone call_{t}	-0.0250	0.0602***	0.0588***	0.0715***	0.0586***	0.0672***
	(0.0198)	(0.0205)	(0.0206)	(0.0247)	(0.0206)	(0.0234)
Rainfall_{t}	0.00779	-0.0669*	-0.0657*	-0.0767*	-0.0731**	-0.0758*
	(0.0341)	(0.0341)	(0.0338)	(0.0394)	(0.0336)	(0.0400)
Excluded instrument		Both	Phone call	Rainfall	Phone call	Rainfall
Kleibergen/Paap F-statistic	27.14	27.14	46.29	11.41	45.56	10.54
Sargan-Hansen J-test (p-val.)		0.307				
Observations	9,609	9,609	9,609	9,609	9,609	9,609

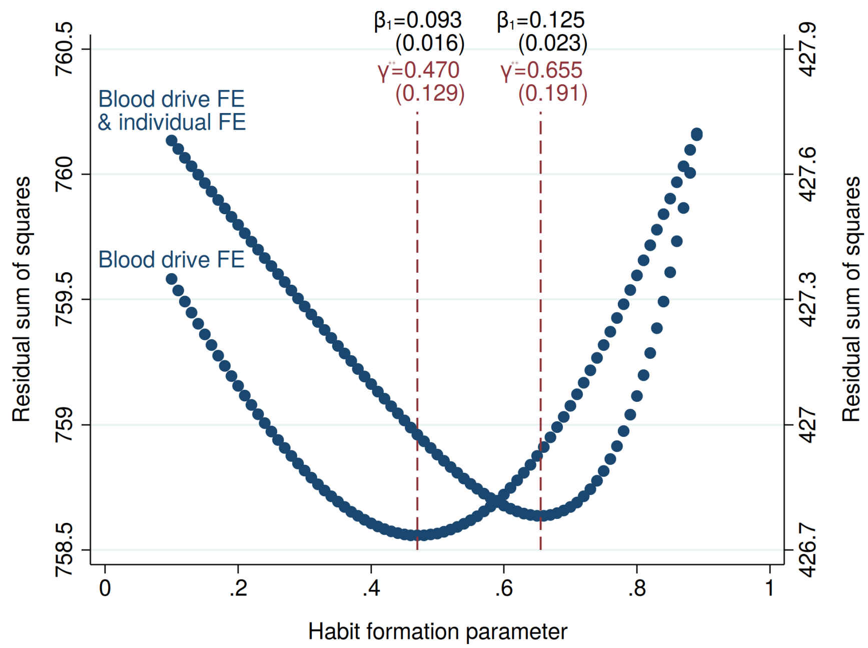
Notes: Regressions additionally include individual controls (gender, age, blood types) and week of the year and sponsor fixed effects. Standard errors clustered at the individual and blood drive level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Appendix D ITT Habit Formation Parameter

Figure D.1 shows the ITT version of Figure 7 of the distribution of γ for the models with blood drive fixed effects and additionally with individual fixed effects, in line with columns (4)-(5) in Table 3. The plot also includes the residual sum of squares to show that the parameters are well identified: in each of the specifications, there is a clear minimum.

The resulting habit formation parameters are 0.470 ($p < 0.01$) and 0.655 ($p < 0.01$), respectively. The estimates are very similar as in Figure 7 and clearly reject the benchmark of no habit formation. Both estimates are also significantly smaller than 1 ($p < 0.01$; $p = 0.04$), thus rejecting a model in which habit formation leads to persistent changes in behavior.

Figure D.1: Grid search of the habit formation parameter



Notes: Relationship between γ and the residual sum of squares. Optimal γ^{**} is chosen to minimize the residual sum of squares. Two-way individual and blood drive cluster robust standard standard errors from 1,000 bootstrap replications in parentheses.

Appendix E The habit formation model with peer effects

In this appendix we show that our strategy for identifying the habit formation parameter γ remains valid in the presence of peer effects among blood donors. We follow Bruhin et al. (2020) and Goette and Tripodi (forthcoming) and add peer effects by augmenting our model to include an additional motivation that is increasing in the propensity to donate p of the other blood donors:

$$u(d_t, S_t, B, \tilde{c}_t) = \begin{cases} \gamma S_t + B + \theta p - \tilde{c}_t & \text{if } d_t = 1 \\ 0 & \text{if } d_t = 0 \end{cases}, \tag{E.1}$$

The parameter θ measures the additional motivation to choose $d_t = 1$ if all other blood donors donated. All other notation remains the same as in Section 6.

Consider K periods: in period $t = 1$, none of the donors have donated in the previous period. Hence, $S_1 = 0$ for all donors. A fraction q of the blood donors is assigned to the treatment condition and asked to donate, as in the baseline model. A fraction $1 - q$ is in the control condition and not asked. In period $t \geq 2$, no intervention happens. They are used to identify habit formation.

Our aim is to show that the strategy to identify habit formation we use remains valid in the presence of peer effects. The reason why this remains possible is that the peer effects affect all donors, in the treatment condition and the control condition, alike and are differenced out in treatment-control comparisons that identify the habit formation parameter.

An individual in the treatment condition will donate if

$$u_1^T = B + \eta + \theta(qp_1^T + (1-q)p_1^C) \geq \tilde{c}_t$$

An individual in the control condition will donate if

$$u_1^C = B + \theta(qp_1^T + (1-q)p_1^C) \geq \tilde{c}_t$$

Peer effects complicate the calculation of optimal donation rates. They solve the system of equations

$$\begin{aligned} p_1^T &= F_c\big(B + \eta + \theta(qp_1^T + (1-q)p_1^C)\big) \\ p_1^C &= F_c\big(B + \theta(qp_1^T + (1-q)p_1^C)\big) \end{aligned}$$

Thus, the treatment effect from asking on donation outcomes in period 1 is given by

$$\Delta p_1 \equiv p_1^T - p_1^C = F_c\big(B + \eta + \theta(qp_1^T + (1-q)p_1^C)\big) - F_c\big(B + \theta(qp_1^T + (1-q)p_1^C)\big) \tag{E.2}$$

As before, if $F_c()$ is uniform (or approximately flat in the relevant region), then

$$\Delta p_1 = \tilde{\eta}$$

where $\tilde{\eta} = \eta f$ is the normalized effect from asking, and f is the density of $F_c()$. Thus, with an approximately uniform distribution $F_c()$, peer effects difference out from the treatment effect.

In period 2, optimal donation rates solve the system of equations

$$\begin{aligned} p_2^T &= p_1^T F_c\big(B + \gamma + \theta(qp_2^T + (1-q)p_2^C)\big) + (1 - p_1^T)F_c\big(B + \theta(qp_2^T + (1-q)p_2^C)\big) \\ p_2^C &= p_1^C F_c\big(B + \gamma + \theta(qp_2^T + (1-q)p_2^C)\big) + (1 - p_1^C)F_c\big(B + \theta(qp_2^T + (1-q)p_2^C)\big) \end{aligned}$$

Just like in the baseline model, we obtain the first step in the recursion

$$\Delta p_2 \equiv p_2^T - p_2^C = \Delta p_1 \Big(F_c\big(B + \gamma + \theta(qp_2^T + (1-q)p_2^C)\big) - F_c\big(B + \gamma + \theta(qp_2^T + (1-q)p_2^C)\big)\Big)$$

If $F_c()$ is approximately uniform, then

$$\Delta p_2 = \Delta p_1 \tilde{\gamma}$$

where $\tilde{\gamma} = \gamma f$ is the normalized habit formation coefficient. Thus, the same recursion follows that the difference in donation rates between the treatment condition and control condition in period k is given by the power function

$$\Delta p_k = \Delta p_1 \prod_{t=1}^{k-1} \Big(F_c\big(B + \gamma + \theta(qp_t^T + (1-q)p_t^C)\big) - F_c\big(B + \gamma + \theta(qp_t^T + (1-q)p_t^C)\big)\Big) \tag{E.3}$$

Thus, with peer effects, the simple recursion that produces a power function in differences of $F_c()$ is only approximately true. These deviations, however, are second order. In the case of an approximate uniform distribution, we again obtain

$$\Delta p_k = \Delta p_1 \tilde{\gamma}^{k-1}.$$