

# Credit when it's due

Timely reminders help consumers reduce their credit card debt

March 2019

---

## Other uses

Enquiries regarding this license and any other use of this document are welcome at:

Managing Director  
Behavioural Economics Team of the Australian Government  
Department of the Prime Minister and Cabinet  
Barton ACT 2600  
Email: [beta@pmc.gov.au](mailto:beta@pmc.gov.au)

The views expressed in this paper are those of the authors and do not necessarily reflect those of the Department of the Prime Minister and Cabinet or the Australian Government.

## Research team

Professor Michael J. Hiscox was the principal investigator for this project. Other (current and former) staff who contributed to the report were: Su Mon Kyaw-Myint, Scott Copley, Ashley Breckenridge, Michael Daffey, and Elizabeth Hobman.

## Acknowledgments

Thank you to the Treasury and Westpac for their support and valuable contribution in making this project happen. In particular, special thanks to Crystal Ossolinski, Lauren Hogan, Laura Llewellyn, and the Westpac Credit Cards team for their work on this project.

The trial was pre-registered on the BETA website and the American Economic Association registry: <https://www.socialscienceregistry.org/trials/2422>

# Who?

---

## **Who are we?**

We are the Behavioural Economics Team of the Australian Government, or BETA. We are the Australian Government's first central unit applying behavioural economics to improve public policy, programs and processes.

We use behavioural economics, science and psychology to improve policy outcomes. Our mission is to advance the wellbeing of Australians through the application and rigorous evaluation of behavioural insights to public policy and administration.

## **What is behavioural economics?**

Economics has traditionally assumed people always make decisions in their best interests. Behavioural economics challenges this view by providing a more realistic model of human behaviour. It recognises we are systematically biased (for example, we tend to satisfy our present self rather than planning for the future) and can make decisions that conflict with our own interests.

## **What are behavioural insights and how are they useful for policy design?**

Behavioural insights apply behavioural economics concepts to the real world by drawing on empirically-tested results. These new tools can inform the design of government interventions to improve the welfare of citizens.

Rather than expect citizens to be optimal decision makers, drawing on behavioural insights ensures policy makers will design policies that go with the grain of human behaviour. For example, citizens may struggle to make choices in their own best interests, such as saving more money. Policy makers can apply behavioural insights that preserve freedom, but encourage a different choice – by helping citizens to set a plan to save regularly.

# Contents

---

<b>Executive summary</b>	<b>4</b>
<hr/>	
<b>Why?</b>	<b>5</b>
<hr/>	
<b>What we did</b>	<b>7</b>
<hr/>	
<b>Results</b>	<b>10</b>
<hr/>	
<b>Limitations</b>	<b>15</b>
<hr/>	
<b>Discussion and conclusion</b>	<b>17</b>
<hr/>	
<b>Appendices</b>	<b>19</b>
<hr/>	
<b>References</b>	<b>40</b>

# Executive summary

---

**People who make only the minimum repayment on their credit card could be paying hundreds of dollars a year in high interest payments. SMS reminders are an effective tool to encourage people to repay more and save money.**

Credit cards give people flexibility, allowing them to make short-term payments they may otherwise have to forgo or delay. Repaying the balance as soon as possible means avoiding high interest charges. Despite such a strong financial incentive, many people consistently repay only the minimum amount—costing them potentially hundreds of dollars more a year.

While many people often simply cannot afford to pay more than the minimum, evidence suggests many others repay only the minimum due to one or more behavioural biases such as status quo bias, present bias, optimism bias, or anchoring. To help, we designed a behaviourally informed intervention to see whether we could encourage consumers to pay earlier and save money.

To test this, we worked with Westpac and the Treasury to design reminder messages, encouraging consumers who consistently pay only the minimum, to repay more. We incorporated words and phrases designed to make the benefits of repaying credit card balances as soon as possible more salient. We then evaluated the effect of these messages using a randomised controlled trial.

SMS reminders had an immediate impact on consumer repayment behaviour, resulting in a \$134 (28 per cent) increase in repayments and close to a one percentage point increase in balance paid in the following month, compared to consumers who received no message. We also found a long-term effect on the balance owed. Consumers who received an SMS reminder had, on average, smaller balances twelve months later. By contrast, there was no such effect from sending email reminders.

The specific content or wording used in the SMS did not seem to matter. Consumers who received any type of SMS reminder increased repayments. Repetition also appeared to have little impact. Sending reminders again in subsequent months did not have the same impact as the initial message.

Our research suggests sending an SMS reminder to consumers before their payment due date can encourage them to make higher repayments. Further research into the message content, timing, and frequency is warranted. In any case, SMS reminders are a simple, cost-effective tool to support consumer decision-making and improve financial wellbeing in the credit card market.

# Why?

---

## **Consistently making low repayments on a credit card can lead to excessive debt and financial distress.**

### **Policy context**

In an effort to help reduce credit card debt, especially among vulnerable consumers, the Commonwealth Government identified a set of proposals in its 2016 consultation paper, *Credit Cards: Improving Consumer Outcomes and Enhancing Competition*. The paper proposed a number of actions, elements of which have been tested by BETA on behalf of the Treasury and in partnership with Westpac. Specifically, BETA developed and tested interventions in line with the paper's recommendations to provide "pro-active assistance for consumers who consistently make small repayments."

Owning and using a credit card is a familiar experience for many Australian consumers. Latest figures show that Australia has around 16 million open credit card and charge card accounts, with total balances of around \$52 billion (Reserve Bank of Australia [RBA] 2018). Of these accounts, two thirds of consumers (around 62 per cent) have just one card, or two at most (Australian Securities and Investments Commission [ASIC] 2018). The average balance per account is around \$3,260 (RBA 2018).

Credit card debt has declined over the last ten years (Australian Banking Association 2018). This may be because credit cards are a relatively expensive form of credit compared to other means (such as personal loans or household mortgages), and amendments to the *National Consumer Credit Protection Act 2009* have had a positive impact on repayment behaviour (Treasury 2016).

### **The problem**

While not all consumers are at high risk of experiencing harm, persistent credit card debt could lead to financial problems and distress for some. Under-repayments on credit card balances can become a problem when consumers spend more money and time on their debt than they originally intended or expected. ASIC (2018) estimates around 435,000 consumers across Australia are making repeatedly low repayments.<sup>1</sup>

---

<sup>1</sup> ASIC (2018) defines "small repayments" as one form of problematic debt, which it describes as instances where "consumers make relatively small repayments for a prolonged period (e.g. the contractual minimum, or amounts near that minimum) [such that] the cost of credit card debt substantially increases, creating risks of financial harm if this occurs regularly."

The longer it takes a consumer to repay their credit card balance, the more money they will owe in interest, in addition to the original debt. This means someone may find themselves with an increasingly large debt to repay over time (for an example, see Fig. 1). Although a person may occasionally repay only the minimum because they cannot afford to repay more, doing so continuously increases their risk of experiencing problematic debt.

Problematic debt can have impacts beyond financial wellbeing. People who experience financial distress have also reported impacts on their physical and mental health and personal relationships (Wesley Mission 2015). For this reason, addressing continual under-repayments is important for preventing debt from snowballing out of control and leading to harm.

Recognising this, the *National Consumer Credit Protection Regulations 2010* (NCCP) requires every credit card statement to include a “minimum repayment warning”. The warning includes a personalised calculation of the length of time and total costs associated with paying only the minimum repayment (NCCP Regulations Reg. 79B). By disclosing this information, regulators hope that greater awareness will motivate consumers to change their repayment behaviour.

Minimum repayment warnings alone may not be enough (Keys & Wang 2019; ASIC 2018; Jones et al 2015; Agarwal et al 2014). This may be because some consumers experience one or more behavioural biases, which warnings have been unable to fully overcome. Our research adds to existing efforts to determine what works in encouraging consumers to repay more than the minimum credit card repayment.

**Figure 1: Example of costs and time to repay balance**

	
Hugh has a credit card with an interest rate of 18.0%	
Hugh's balance is \$3,000	
If Hugh pays only the <b>minimum repayment</b> , he would <b>pay \$9,521</b> and spend <b>25 years</b> paying it off <sup>2</sup>	
If Hugh repays just a few per cent <b>more than the minimum</b> , he could <b>save \$5,980</b> and pay off his balance in just <b>2 years</b>	

Note: Example based on average balances and interest rates using the ASIC [MoneySmart credit card calculator](#)

<sup>2</sup> As of 1 January 2019, banks and credit providers must make an assessment of a consumer's ability to repay their credit card balance within three years. This aims to prevent consumers from spending excessive periods of time repaying their balance, but it does not preclude consumers from making low minimum repayments.

# What we did

---

## We tested the effect of different reminder messages on credit card repayment behaviour.

### Credit card repayments may be affected by behavioural biases such as status quo bias, present bias, optimism bias, and anchoring

In many financial decisions, consumers may display present bias, thinking their future self will control expenditure while their current self makes purchases for immediate gratification. For example, we know present-biased borrowers often end up over-borrowing and pay more in interest in the long run (Heidhues & Koszegi 2010). This can be compounded by optimism bias, where consumers overestimate the likelihood they will be able to repay a debt (Doyle 2018). A credit card's interest rate can initially seem irrelevant to consumers who optimistically believe they will pay off their balance each month.

The way consumers receive information about their repayment requirements can affect their behaviour. While minimum repayment requirements help ensure consumers pay off at least some of their credit card balance, they can also have the unintended effect of acting as a psychological anchor. The minimum repayment becomes a reference point from which consumers make their repayment decision, rather than basing their repayments on their ability to repay and the interest costs they could avoid (Adams et al 2018; Navarro-Martinez et al 2011; Stewart 2009).

#### Box 1: Behavioural concepts relevant to credit card repayments

**Anchoring** is the tendency to rely heavily on reference points or prices when making decisions.

**Framing** something as either a loss or gain can affect our decisions, even if the magnitude of the loss and gain are the same.

**Optimism bias** is the tendency to overestimate our ability to complete a task or follow through with our intentions.

**Present bias** is the tendency to engage in actions leading to short-term benefits that do not align with our long-term interests.

**Social norms** are the behaviours considered acceptable in a group or by society, which often have a strong influence on people's decisions.

**Status quo bias** describes our tendency to stick with our current course of action, even if we intend to or would benefit from change.

It's also likely that consumers are affected by status quo bias. In finance, many consumers benefit from "set and forget" payments such as direct debit, which allow them to make regular

payments without having to remember to do so every time. While this can be beneficial in many ways, the tendency to stick with our usual course of action can also mean consumers miss out on benefitting from changes. It is possible many consumers who consistently repay only the minimum amount on their credit card balance are stuck in a cycle or habit of making low repayments.

To combat some of these behavioural biases, which may prevent consumers from paying off more of their credit card balance, we considered whether sending a timely reminder could have an impact on repayment behaviour. We also considered whether the mode of communication and the content of the reminder message affected consumer behaviour.

### We designed messages to encourage consumers to make higher repayments

The simple act of sending a reminder may help make the issue of repayment (and the amount repaid) more salient for the consumer, helping to overcome inattention and reliance on simple heuristics such as “pay the minimum due.” Additional phrases evoking either social norms or loss framing aimed to help consumers overcome any perceptions that repaying only the minimum was common or costless.

We tested whether the inclusion of the phrase “avoid paying more interest” was effective at invoking loss aversion and prompting higher repayments. We also drew on social norms to test whether describing the higher repayments of “many people” would encourage higher repayments. Finally, we varied the use of the stronger term, “debt”, and the more business-as-usual term, “balance” (see Fig. 2). By designing the messages this way, we

**Figure 2: SMS type**

<p><b>Control group: No message</b></p> <p>Consumers assigned to the control group didn't receive any behavioural messages and experienced business-as-usual as a Westpac customer.</p>	<p><b>Attention control group: Short message</b></p> <p>“Hello Name, Payment on your Westpac credit card is due next week.”</p>
<p><b>Loss framed + word ‘balance’</b></p> <p>“Hello Name, Payment on your Westpac credit card is due next week. To <b>avoid paying more</b> interest, think about lowering or even clearing your full <b>balance</b>.<sup>3</sup> Every extra amount can help.”</p>	<p><b>Loss framed + word ‘debt’</b></p> <p>“Hello Name, Payment on your Westpac credit card is due next week. To <b>avoid paying more</b> interest, think about lowering or even clearing your full <b>debt</b>. Every extra amount can help.”</p>
<p><b>Social norming + word ‘balance’</b></p> <p>“Hello Name, Payment on your Westpac credit card is due next week. <b>Many people</b> choose to pay the full <b>balance</b> on time. Every extra amount can help.”</p>	<p><b>Social norming + word ‘debt’</b></p> <p>“Hello Name, Payment on your Westpac credit card is due next week. <b>Many people</b> choose to pay the full <b>debt</b> on time. Every extra amount can help.”</p>

<sup>3</sup> Note that words in bold here emphasise the differences between messages. In the actual delivery of the SMS, none of the words were bolded.

hoped to help overcome any status quo bias, present bias, optimism bias, or anchoring consumers may be experiencing.

In order to see if the message delivery channel matters, consumers were split into two cohorts based on their preferred communication channel. One cohort received our messages via SMS, and the other via email. If consumers had provided contact details for both channels, they were assigned to the email cohort to help bolster our sample size for the email trial. For both the SMS and email cohorts, consumers were randomly assigned to either the control group, the short message group, or to one of the four alternative message groups (with an equal number allocated to each group). Individuals who received a message got their SMS or email at least seven days before their credit card payment was due.

### **We tested our messages using a randomised controlled trial**

We worked with Westpac, a large Australian bank, to test the impact of our messages using a randomised controlled trial. Westpac selected around 24,000 credit card holders who had consistently made low repayments for the previous 12 months (for a full description of our selection criteria and the trial design generally, see Appendix A.) We also recorded whether consumers had a Rewards credit card or a non-Rewards credit card. Consumers with Rewards cards receive additional benefits, such as frequent flyer points, but they also have a shorter interest-free repayment period (45 days, rather than 55 days for non-Rewards card holders). They also typically have higher interest rates.

Prior to the trial starting, we pre-registered the study, including the analysis plan with our key hypotheses and the main outcomes we would assess. Our two main outcomes were the amount in dollars that credit card holders repaid and the percentage of balance repaid. We hypothesised receiving any message (including the short message) would increase repayments compared to counterparts in the control (no message) group. We also hypothesised receiving a message incorporating either loss framing or social norms would generate a greater increase in repayments than the short reminder message, and that the word “debt” would increase repayments to a greater extent than the word “balance”.

To test if consumers benefitted from repeated messages, we sent the same message to each consumer in each of the treatment groups three times over the course of the trial: month 1 (June), month 3 (August) and month 5 (October) of the trial. Westpac collected monthly payment and balance data on the consumers enrolled in the trial. Data was collected for 12 months to enable us to assess the long-term impacts of our messages.

#### **Box 2: What is a randomised controlled trial?**

Well-designed randomised controlled trials (RCTs) provide the best empirical method for determining a policy's quantifiable impacts. In this respect, RCTs are considered the 'gold standard' for impact evaluation. RCTs work by randomly separating people into two or more groups, in a manner similar to flipping a coin. People in a 'treatment' group receive an intervention (new policy) while people in the 'control' group receive the business as usual experience. On average, the difference in outcomes between people in a treatment group and in the control group reflects the causal impact of the new policy.

# Results

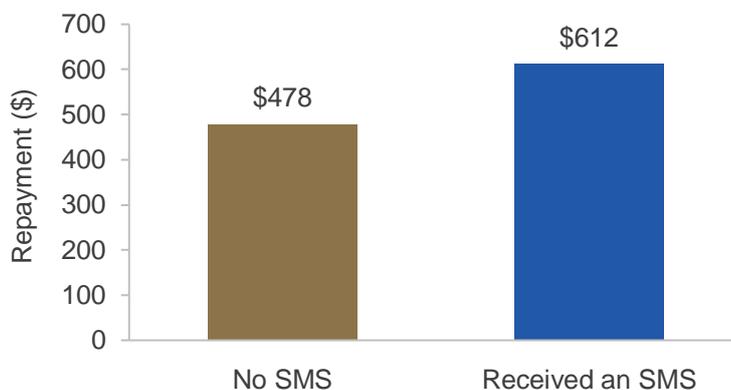
**Timely and personalised SMS prompts increased credit card repayments among consumers who previously paid the minimum. Those receiving an SMS paid, on average, an extra \$134 off their credit card.**

## SMS messages worked better than emails

Overall, credit card holders who received a reminder message repaid more than those who did not. This increase in repayments was driven by our SMS messages, with emails having no apparent impact.

For the SMS population, the control group made an average repayment of \$478, or 5.4 per cent of their balance. Those who received an SMS repaid \$612, or 6.2 per cent of their balance in the month following (Figure 3; see also Appendix B, Table 4). This is an increase of \$134, or 28 per cent, in repayments and close to a one percentage point increase in balance paid. Both of these increases are statistically significant.<sup>4</sup>

**Figure 3: Sending SMS messages increased credit card repayments<sup>5</sup>**



Primary outcome (n=14,591). The SMS group repaid \$134 more than the control group ( $p < 0.0001$ ). We found similar results for the change in the percentage of the balance paid.

<sup>4</sup> There is ongoing academic debate about how (or whether) to test for statistical significance (Wasserstein & Lazar, 2016). When we state a result is 'statistically significant', this means we judge the result to be a real effect, not a chance finding. Our assessment is based on, amongst other things, the 'p-value', the effect size, consistency with past evidence and theory, and any deviations from our pre-analysis plan. Where such assessments are finely balanced, we signal this in the text.

<sup>5</sup> We analysed results for both primary outcome variables – repayment amounts and the percentage of balance repaid. In this section, we often just report on one outcome variable for simplicity. The full results, including effect sizes, p-values and confidence intervals, are reported in Appendix B.

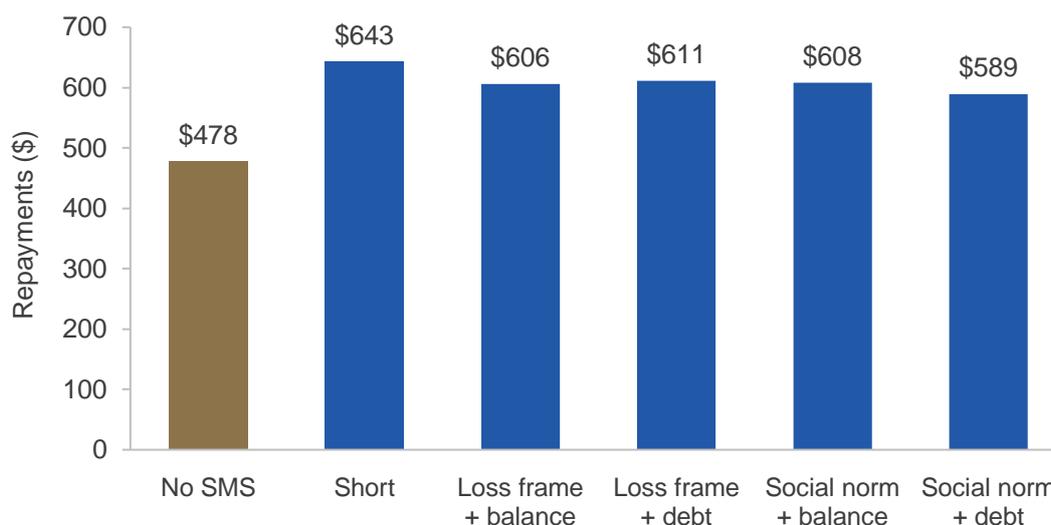
In contrast, for the email population, the control group made an average repayment of \$669, while those who received an email repaid \$653.<sup>6</sup> This difference is small and not statistically significant. We deliberate on this result further in the Discussion section. The remainder of this section focuses on the effects of the SMS messages.

### Varying the message had little effect

We sent five different SMS messages (see “What we did” section for a full description). All messages, including the short SMS, caused an increase in repayments compared to the no-SMS group (Figure 4). These estimated increases in repayments ranged from \$111 to \$165 and all were statistically significant, with p-values below 0.017.

When we compared the five SMS variations to each other, we found small differences in the estimated repayment amounts. Statistical testing revealed, however, these differences were likely due to chance (see Appendix B, Table 4). On balance, the short message worked as well as our more complex messages.

**Figure 4: All SMS variations increased payments, but there was little difference between them**



Primary outcome (n=14,591). All SMS groups are statistically significantly different from the no-SMS group but not statistically significantly different from each other. We found a similar pattern of results for the change in the percentage of the balance paid (see Appendix B, Table 4).

### The effect of the first message persists but the effect of follow-up messages is uncertain

The first message reduced the balance owing in subsequent months. This had a flow-on impact on the minimum repayment due and this may have reduced the average repayment in subsequent months. To take this flow-on effect into account, for our month-by-month comparisons we switch our focus from average repayment amounts to our other primary

<sup>6</sup> Control group repayments were higher in the email cohort (\$669) compared to the SMS cohort (\$478). We assume this is due to differences in the characteristics of the two cohorts. In particular, credit card balances were higher among the email cohort, meaning the minimum due was also higher. See Appendix B, Table 2 for demographic statistics for the SMS and email cohorts.

outcome variable – the percentage of balance paid – because this takes into account changes in balance from the previous month.

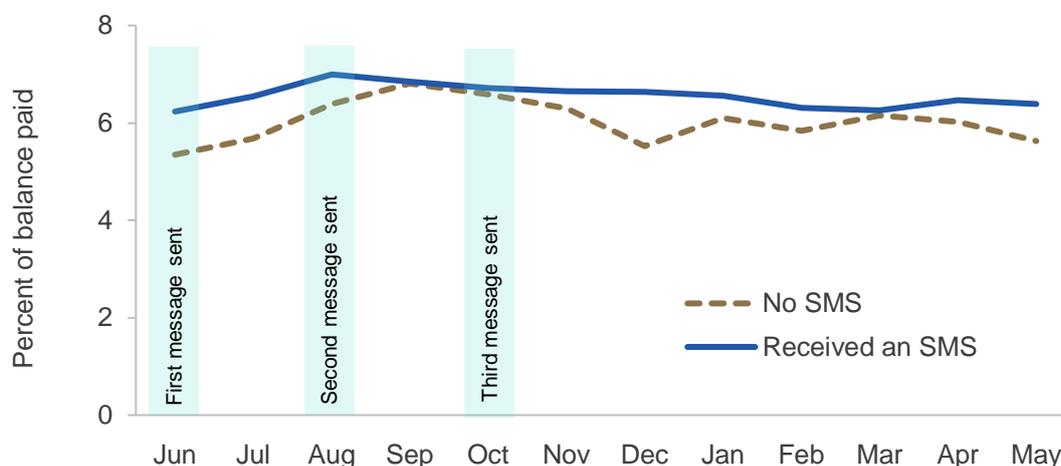
Messages sent in the first month of the trial continued to have an effect in the second month, causing a 0.9 percentage point increase in balance paid (5.7 per cent versus 6.5 per cent,  $p=0.01$ ) or a \$78 increase in raw payments (\$495 versus \$573,  $p=0.03$ ; Figure 5).

We sent repeat SMS messages to the same groups in month 3 (August) and month 5 (October) of the trial. In August, we saw a 0.6 percentage point increase in balance paid over the control (6.4 per cent versus 7.0 per cent) however this effect is not statistically significant at standard levels ( $p=0.14$ ). We did not see a meaningful difference in the raw dollar amount paid for this month. However, taken with the strong results from month one and two, we think this is suggestive of an effect, due to either a persistent effect of the first message or an effect of the second message (or a combination of both).

We found no meaningful difference in the percentage of balance repaid in October. This suggests that by this point, consumers had paid all the additional balance that they were able to or that consumers became desensitised to the messages. There also appears to be a substantial difference in balance repaid of 1.1 percentage points in December, however we suspect this is a chance occurrence.

See “Additional detail on the time series analysis” in Appendix A for more discussion of the results over time.

**Figure 5: Effect of SMS messages over time, percentage of balance paid**



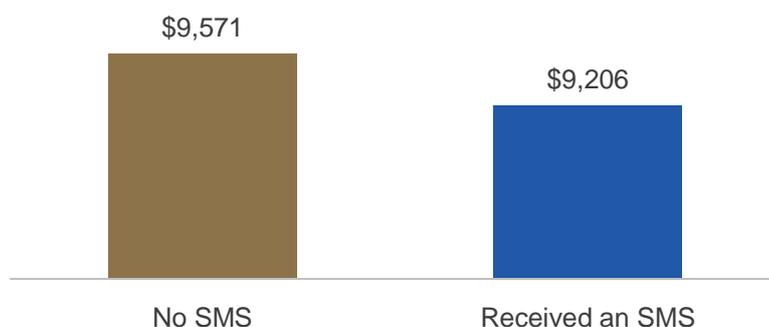
Primary outcome ( $n=14,591$ ). This graph shows monthly repayments as a percentage of the balance owing. SMS messages were sent in June, August, and October. While the first SMS had a strong effect and there is weak evidence to support an effect of the second message, the third SMS did not have a detectable effect.

### Our messages had a long-term impact on people’s finances

We wanted to know if sending messages had lasting impact on the financial status of credit card consumers or if increases in repayments were offset later by reduced payments or increased expenditure. To this end, we conducted exploratory analysis on the balance owing at six and twelve months after the first SMS was sent. At six months, those who received a

message had balances \$249 lower on average than those who did not receive a message (\$10,374 versus \$10,623). At twelve months, this result was even more pronounced, at \$365 (\$9,206 versus \$9,571; Figure 6).

**Figure 6: Receiving an SMS results in a lower balance after twelve months**

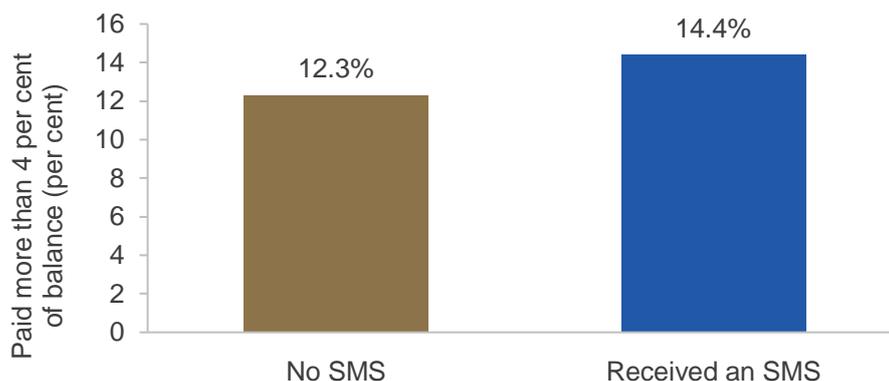


Exploratory analysis (n=14,591). This figure illustrates the average balance after twelve months. Receiving an SMS caused a decrease of \$365 in the balance owing at twelve months (p=0.008).

### The intervention worked by encouraging some to make large payments

We also looked at the percentage of individuals who paid more than four per cent of their balance in month 1 (June) of the trial, since this was the repayment threshold used to define the trial population. In the no-SMS group, 12.3 per cent of consumers paid more than four per cent of their balance, while in the SMS group this was 14.4 per cent (Figure 7).

**Figure 7: Proportion who paid more than 4 per cent of balance**



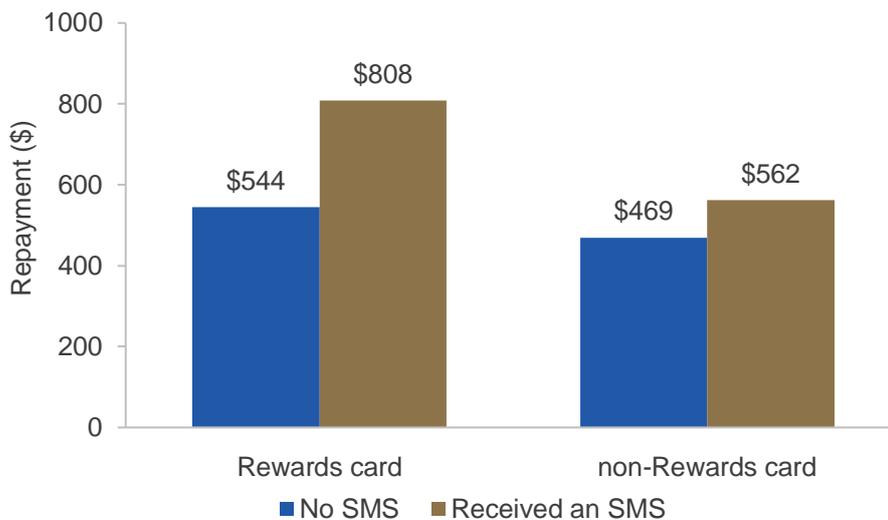
Secondary outcome (n=14,591). This figure illustrates the proportion of consumers in each group repaying more than four per cent of their balance in month 1 (June). Receiving an SMS caused an increase of 2.1 percentage points (p=0.005).

These results seem to imply our SMS messages caused a small group of consumers to make large repayments. However, on their own, these results are not conclusive. To investigate this further, we compared the distribution of repayments for the no-SMS and SMS groups. This additional analysis suggested the increase in repayments was indeed due to a small number of individuals increasing their repayments substantially, and so the intervention may work best for those with the resources to make larger repayments.

### The message appeared to work better for Rewards card holders

We found, in exploratory analysis, the impact of SMS reminders on Rewards card holders seemed to be the main driver of our overall findings. Among those with a non-Rewards card, the message group repaid \$92 more, whereas for those with a Rewards card, the treatment caused a \$264 increase (Figure 8; Appendix B, Table 9). In other words, the impact of the SMS message was \$172 larger for Rewards card holders ( $p=0.04$ ). This was sufficiently large that we judge it to be statistically significant even though this was exploratory analysis.

**Figure 8: SMS messages appeared to work better for Rewards card holders**



Exploratory analysis (Rewards card holders  $n=2,322$ ; non-Rewards card holders  $n=11,873$ ). For Rewards card holders, the SMS group repaid an extra \$264 compared to the control group ( $p=0.0003$ ) whereas the non-Rewards card holders repaid an extra \$92 ( $p=0.017$ ). The difference in these effects was \$172 ( $p=0.04$ ). We found similar differences in the percentage of balance paid although the  $p$ -values were higher ( $p=0.004$ ,  $p=0.2$  and  $p=0.05$ , respectively).

We found no evidence that the treatment worked better among different age groups. This supports earlier ASIC research, which found that consumers who frequently make only minimum repayments on their credit card debt fall relatively evenly across age groups (ASIC 2018, 28). Nor was there a difference between males and females or those with higher credit limits (Appendix B, Table 9).

# Limitations

---

## **We made a lot of comparisons but we took account of this in our interpretation of the results**

In this trial we sent messages by both SMS and email, sent five different messages on three occasions, and collected monthly data for a year. This leads to many potential comparisons. The more comparisons made, the more chance there is of finding an effect due to chance.

We took a number of steps to reduce the risk of false-positive findings. In our analysis plan, we pre-specified a decision-tree approach, similar to the approach recommended by Yadav & Lewis (2017). For example, once we found emails had no effect in the first month, we made no further comparisons involving emails. We followed the same approach when our SMS variations showed no difference. We were also careful when interpreting findings that were inconsistent over time, or findings that were unexpected. Finally, for our main findings, we found larger-than-expected effect sizes coupled with small p-values, which gives us confidence in the findings we report.

## **We made some adjustments for outliers and missing values**

We found some outliers in the data, such as a small number (about 1.8 per cent) of customers who repaid more than the full balance owing. We truncated these repayments to be equal to the balance owing. Similarly, these over-payments resulted in a negative balance owing in subsequent months, implying that a *positive* repayment resulted in a *negative* percentage of balance repaid. To remove such perverse outcomes, we truncated these percentages to zero. In both cases, robustness checks showed the truncation had little impact on the results.

Some consumers' accounts became inactive, closed, or defaulted during the course of the trial or before it began. We kept these consumers in our dataset during analysis and set missing values to zero. For a full discussion of data adjustments, missing values and related robustness checks, see Appendix A.

## **Care should be taken before generalising our results**

Our study targeted a particular group of consumers – those with consistently low repayments. Consequently, our results may not generalise to the average credit card consumer. For a comparison of the characteristics of our trial population and the general credit card consumer population, see Appendix A.

## **Some consumers received a message earlier than others**

Consumers in our trial held cards with different repayment periods and this meant there was some variation in when they received a message. For example, a Rewards card has a 45-day interest-free period whereas it is 55 days for non-Rewards cards. We were unable to determine whether the timing of the message, relative to a consumer's payment due date, influenced the effectiveness of the message. See Appendix A for further discussion.

## Choice of outcome variables

We studied two outcome variables – repayment amounts and the percentage of balance repaid. Repayment amounts are simple and easy to interpret but, as noted in the Results section, may be less suitable for month-by-month comparisons. Higher repayments in the first month will, all else equal, reduce the balance owing and, as a consequence, also reduce the minimum repayment due and likely average repayments in subsequent months. To deal with this, we also measured payments as a percentage of balance. In general, we expect these two outcomes to be closely related so we place the most weight on findings where they point in the same direction. We were more cautious in cases where the two outcomes diverge.

# Discussion and conclusion

---

**How we communicate matters when prompting people to repay more than the minimum due on their credit card. Further research can help clarify what aspects of the communication work best.**

## **Sending SMS reminders helped people repay more of their balance**

Receiving a reminder prompted consumers to increase their repayment in the first instance. These reminders also have a lasting effect on the size of people's balances. Those who received SMS maintained a smaller balance six and even twelve months later compared to those who received no messages.

We know SMS reminders often have an impact on behaviour. For example, BETA's other trials on [improving on-time reporting](#) and [reducing customer uncertainty](#) have successfully used SMS reminders to help people who rely on government services. In this trial, we focused on a cohort of people who had repeatedly repaid at or near the minimum for such a long period (at least 12 months) that an unexpected prompt could have triggered them to overcome their tendency to stick with the status quo. Our reminders made the repayment more salient, commanding their attention.

## **We observed little apparent effect from follow-up messages**

If consumers had been meaning to repay more and simply needed a timely prompt to finally make the switch to higher repayments, one SMS may have been sufficient. Likewise, if consumers had simply never considered repaying more than the minimum, learning this once may be enough for it to make a lasting difference.

The timing of messages may also explain the difference in the effect for those with Rewards cards. Rewards cards have shorter payment cycles, so these consumers received an SMS closer in time to when they also received their credit card statement, than those with non-Rewards cards. However, there could also be other explanations for this difference (such as engagement in the credit card market, or credit history), which further research could help to explain.

## **The content of messages did not have an impact**

We were surprised to find little variation between our behaviourally informed messages and that these messages performed no better than our "short" SMS. The behavioural elements could have been less impactful because they appeared later in the message and may not have been read. When an SMS notification appears on most screens, viewers often see only

the first line of text. Some people may never have read the message in full, missing the additional wording that used social norms or loss-framing to encourage repayments. It's also possible there is simply no effect of social norms or loss-framing on repayment behaviour.

We think it's more likely one SMS was sufficient because people needed a single, unexpected prompt to follow through with their intentions to devote cognitive effort to the issue and repay more than they had in the past. As such, the reminder itself could be the driving factor regardless of its content.

### **SMS outperformed emails as a mode of communication**

We were expecting SMS and email messages to have similar impacts, but we did not find evidence suggesting emails had an effect. Emails could be an ineffective mode of communication for encouraging repayment behaviour, or were less likely to be read. Emails from commercial entities can be filtered directly into junk folders or disregarded as a scam, and so could be less likely to be opened or read compared to an SMS message. For example, data from Westpac suggests 60 per cent of their emails on average, are opened.

However, this doesn't necessarily rule them out as a mode of communication. Some consumers opt to receive emails as their preferred method of communication, and this may make them different from consumers who want SMS only or have no preference between the two. Further testing may reveal more information about what timing and phrasing of emails is most effective for reaching these consumers. In the meantime, timely SMS reminders for those who have opted for this mode of communication may be an effective tool for encouraging higher repayments.

### **Simple, low-cost solutions can make a significant difference**

Overall, a lot of focus has been given to finding ways to help people pay less interest. Helping consumers save money is important for their financial wellbeing, but the impacts extend beyond the immediate benefits of avoiding higher interest charges today. Preventing long-term debt from becoming problematic can help ensure fewer credit card consumers experience financial distress and instead benefit from the flexibility credit cards can provide.

While no one strategy is a silver bullet, our research suggests targeted, individual-level solutions can make a difference. Efforts to raise awareness in Australia have mostly focused on warnings, which make salient the downsides of repaying only the minimum. Our research builds on these efforts, and demonstrates how something as simple as a timely SMS reminder can have a lasting impact on repayment behaviour.

# Appendices

---

## Appendix A - Technical Details

### Overview

We conducted a randomised field experiment in partnership with Westpac, a major Australian bank. The unit of randomisation was individual credit card customers. We randomly assigned these customers to receive no message (control) or one of five messages via either SMS or email.

Westpac sent the first message in five batches between 30 May 2017 and 1 July 2017. Delivery was staggered in this way to ensure messages arrived after the cardholder's statement date and before payment was due. The bank sent follow-up messages at two and four months after the initial message. Payment and balance were monitored for each individual on a monthly basis for 12 months after the first message was sent.

### Pre-registration, pre-analysis plan and ethics.

We pre-registered this trial on both the American Economic Association RCT Registry (RCT ID no. AEARCTR-0002422) and the BETA website after the trial had commenced but prior to receiving or analysing any data on outcomes. This pre-registration includes a detailed pre-analysis plan containing details for our proposed analysis, including our research hypotheses. We made three major deviations from our original analysis plan.

First, we did not anticipate that the effect of the reminders would be dependent on channel (email or SMS). However, after finding that messages sent by email had no apparent effect, we focused all subsequent analyses on those who received SMS messages. We think this is justifiable given the strong effect (both in magnitude and statistical significance) of the SMS messages and because we powered the trial adequately to detect small effects in the SMS group (see the "Power calculations and sample size" section below). After shifting our focus to the SMS group, we no longer considered comparisons involving the email group part of the primary analysis. This reduced the number of comparisons made.

Second, because there was no apparent difference in the effect of SMS variations at month one, all subsequent comparisons focused on the control group versus the five variations combined. Again, this reduced the total number of comparisons made. Although we did not pre-specify this approach, it is consistent with the decision-tree approach set out in our pre-analysis plan.

Third, we made some adjustments to our outcome variables to account for cases where consumers paid more than the balance owing. We hadn't anticipated such cases but have provided our rationale for these adjustments, along with robustness checks, in the 'Adjustments to outcome data' section below.

The project was approved through BETA's ethics approval process, with risk assessed in accordance with the guidelines outlined in the National Statement on Ethical conduct in Human Research

## Outcomes

As specified in our pre-analysis plan, we focused on two outcomes. We classify effects that are practically meaningful and statistically significant on both outcomes to be strong evidence, with a positive finding on only one outcome regarded as weak evidence. Our outcomes were:

- monthly repayment in dollars,
- monthly repayment as a percentage of the monthly balance.

In our tables, we report one pre-registered secondary outcome - the proportion of individuals paying above four per cent of their balance. We also report balance at 6 and 12 months to give a sense of the cumulative impact of the trial. This outcome was not pre-registered and accordingly we treat the results as exploratory.

## Population and sampling

The population of interest for this trial was credit card consumers who persistently paid a low proportion of their balance. We drew our sample from customers of a major Australian bank; customers meeting the following criteria were enrolled:

- held a credit card for at least one year,
- paid 2 to 4 per cent (inclusive) of their credit card balance for at least 10 out of the preceding 12 months, and for each of the most recent 3 months,
- had a credit card balance of greater than or equal to \$500 the month before the trial, and
- incurred interest charges of greater than or equal to \$25 the month before the trial.

We excluded those with recent balance transfers, those who had failed to repay the minimum amount of their balance or had written off accounts, and those who were deceased or involved with legal problems. This gave us a final trial sample of 24,053 consumers.

The following table shows the difference in credit card usage between our trial sample and the broader Westpac credit card consumer population.

Trial and non-trial credit card consumer characteristics		
	All Westpac credit card consumers	Trial sample (pre-trial)
<b>Average credit card balance</b>	\$3,134	\$11,527
<b>Average repayment</b>	\$1,900	\$277
<b>Average credit limit</b>	\$11,111	\$14,420

## Power calculations and sample size

We used 12-months of pre-trial data from February 2016 to January 2017 to perform power calculations prior to the trial starting. For our payment amount outcome, we calculated that with a significance level of 5 per cent, we had 80 per cent power to detect a \$22 increase in the email channel with 1,524 people per group, and an \$18 increase in the SMS channel with 2,394 people per group. These calculations were based on expected repayments of \$294 without any intervention. These sample size estimates are close to our final trial sample.

## Stratification and randomisation

The final trial sample consisted of 24,053 consumers who were split into two groups: (1) those who were registered to receive only email correspondence; and (2) those registered to receive SMS correspondence. This resulted in a total of 9,462 consumers in the email group and 14,591 consumers in the SMS group. Within the email and SMS groups, we then stratified individuals into nine strata based on their age and credit card balance. Within each stratum, consumers were randomly assigned to each of the six trial arms with equal probability. See Appendix B, Table 1 for the number in each treatment group.

The bank implemented stratification, randomisation and data extraction procedures using SAS.

## Method of analysis

The principal analysis of the effect of the intervention was a covariate-adjusted comparison of our primary outcomes across the treatment and control groups. This estimate, confidence intervals (CI) and p-values were derived from a linear regression model with the following specification:

$$y_{ij} = \alpha + \tau T_i + \beta x_i + \gamma x_i T_i + \epsilon_i$$

Where  $\alpha$  is the intercept,  $T_i$  is a vector of indicators for treatment group membership,  $x_i$  is a vector of mean-centred strata indicators and covariates,  $x_i T_i$  is an interaction between treatment group indicators and the mean-centred strata indicators and covariates, and  $\epsilon_i$  is an error term. We included the following covariates: average monthly repayments over the 12 months preceding the trial, and an indicator for sex. These variables, along with our strata indicators, were interacted with the treatment indicator as per Lin (2013). All analyses were intent-to-treat.

We used robust standard errors (HC2) for all analyses. We have not made adjustments for multiple comparisons; however, we provide all relevant statistics to enable readers to make these adjustments if required. We conducted our analyses using R 3.5.2 and STATA 15.

## Adjustments to outcome data

Some individuals made payments larger than their balance. In month 1 (June), there were 424 such cases, around 1.8 per cent of the trial population. These 'over-payments' could occur for various reasons, for example, if consumers make a pre-payment before a large expense or before making a cash withdrawal (e.g., while travelling), if they make the full payment for their balance plus any expenditures incurred after the balance due was calculated, or simple user error where they accidentally paid more than they needed or intended.

None of these over-payment scenarios reflected the cases that we hoped to influence through our reminder messages; instead, they were likely to just add noise to the data. Therefore, we truncated the repayment amount so that it was equal to the balance owing. Thus, the percentage of balance repaid was capped at 100 per cent. We ran a robustness check without truncation and found that it made little difference to the results (see Appendix B, Table 7).

Repayments that were equal to the balance owing could result in a zero balance for the following month (assuming that no further expenditure was incurred in the interim). This created a difficulty for our second primary outcome – percentage of balance paid – since it required division by zero. In these cases, we set the percentage of balance paid to zero.

Finally, repayments that were larger than the balance owing could result in a negative balance for the following month (assuming that little or no further expenditure was incurred in the interim). This implied that any non-zero repayment would, perversely, produce a *negative* percentage of balance paid. Instead, in these cases, we set the percentage of balance paid to zero. This is consistent with the truncation for over-payments: we treated any overpayments as if they had simply paid off the full balance and so their subsequent balance owing was reduced to zero. Again, we ran a robustness check without truncating the negative values and found that it made little difference to the results (see Appendix B, Table 7).

### **Missing values**

During the course of the trial, some individuals closed their accounts, defaulted, or their accounts became inactive. In these cases, where payment and balance data were no longer available, we set payment and balance to zero.

Separately, some trial participants were randomised into the trial but were excluded from receiving a message before trial launch for various reasons (for example, if the card was lost or stolen, or there was suspected fraud). Those assigned to treatment in this cohort did not receive a message. We were still able to obtain payment and balance data on these individuals and thus included them in our intent-to-treat analysis.

### **Subgroup analyses**

We did not preregister subgroup analyses, nor did we power the study to detect effects in subgroups. Thus, we treat our subgroup findings with caution.

We pooled our five SMS messages for this analysis. We then ran regressions within subgroup levels to estimate conditional average treatment effects (CATEs). In order to estimate the difference between CATEs and test for significance, we ran regressions in which we interacted an indicator for subgroup membership with an indicator for treatment.

Consumers in our trial held either a Rewards card or a non-Rewards card. Those using a 45-day Rewards card have a shorter repayment period than those with a 55-day non-Rewards card, and this meant there was some variation in when they received a message. In addition, those with 45-day cards tend to have larger saving balances than those with 55-day cards and may have better credit histories or a higher propensity to be actively engaged in the credit card market given the special features of their reward card. These factors may make them more likely to respond to a message about increasing repayments.

The difference in the repayment periods between the cards means some consumers received our message soon after receiving their credit card statement, while others received it later,

closer to their payment due date. Our trial suggests those with a Rewards card made higher repayments than those with a non-Rewards card in response to our SMS. Given the range of differences in these card holders discussed above, it is not possible to attribute this to receiving a message within closer proximity of their payment due date. The merits of sending an SMS prompt closer to payment due date is therefore worthy of further investigation.

### **Additional detail on the time series analysis**

In month 2 of the trial, we report a 0.9 percentage point increase in the per cent of balance paid ( $p = 0.01$ ) and an increase in repayments of \$78 ( $p = 0.03$ ). The number of statistical tests performed in this study means we are more likely to find p-values less than 0.05 by chance, so taken alone the reported p-values do not constitute good evidence of an effect. However, because of the strong impact of our treatment in month 1, and because the effect size for both outcomes in month 2 was still large, we deem the results at month 2 to be meaningful.

We are inclined to discount the December results as a chance occurrence as we cannot think of a mechanism by which an SMS delivered in October (which had no effect at this time) could generate an effect in December. We performed a robustness check on this result and found that it was unusually sensitive to the inclusion/exclusion of a small number of outliers.

## Appendix B – Key Statistical Tables

This appendix presents the statistical tables which underlie the results section. It includes detail not included in the main body of the report. Specifically, we present:

- pre-randomisation characteristics of trial participants by treatment group (Table 1) and by communication channel (Table 2), and unadjusted balance/payment amounts for each month of the trial (Table 3).
- the results of the primary analysis – this includes the effect of sending any message among the email and SMS groups and both channels combined (Table 4), SMS message variations compared to control (Table 5), and to each other (Table 6). We also present comparisons at Month 1, 2, 3 and 5 of the trial (Table 7).
- exploratory analyses: balances at 6 and 12 months (Table 8), and subgroups (Table 9).

**Table 1 : Baseline characteristics of trial participants**

	Control	Short	Loss frame + balance	Loss frame + debt	Social norm + balance	Social norm + debt	Total sample
<i>n</i>	4,001	4,004	4,017	4,008	4,004	4,019	24,053
Communication channel							
Email	39.3% (1,574)	39.3% (1,573)	39.4% (1,582)	39.3% (1,577)	39.3% (1,573)	39.4% (1,583)	39.3% (9,462)
SMS	60.7% (2,427)	60.7% (2,431)	60.6% (2,435)	60.7% (2,431)	60.7% (2,431)	60.6% (2,436)	60.7% (14,591)
Age							

**Table 1 : Baseline characteristics of trial participants**

45 or less	29.3% (1,174)	30.0% (1,203)	29.0% (1,164)	29.5% (1,181)	29.1% (1,165)	29.2% (1,173)	29.4% (7,060)
> 45	70.7% (2,827)	70.0% (2,801)	71.0% (2,853)	70.5% (2,827)	70.9% (2,839)	70.8% (2,846)	70.6% (16,993)
<b>Sex</b>							
Female	45.4% (1,817)	44.0% (1,763)	44.6% (1,790)	44.6% (1,788)	45.4% (1,817)	43.5% (1,748)	44.6% (10,723)
Male	54.6% (2,184)	56.0% (2,241)	55.4% (2,227)	55.4% (2,220)	54.6% (2,187)	56.5% (2,271)	55.4% (13,330)
<b>Card type</b>							
Rewards	16.0% (642)	17.0% (679)	17.9% (719)	17.7% (711)	17.9% (715)	17.6% (709)	17.4% (4,175)
Non-Rewards	83.1% (3,326)	80.1% (3,206)	79.3% (3,185)	78.6% (3,151)	78.8% (3,156)	79.0% (3,175)	79.8% (19,199)
Missing	0.8% (33)	3.0% (119)	2.8% (113)	3.6% (146)	3.3% (133)	3.4% (135)	2.8% (679)
<b>Interest rate</b>							
13.49%	45.2% (1,808)	44.1% (1,765)	44.0% (1,769)	43.0% (1,722)	42.8% (1,713)	42.5% (1,708)	43.6% (10,485)
15.99%	17.9% (715)	17.1% (684)	16.0% (644)	17.7% (710)	17.1% (684)	16.5% (663)	17.0% (4,100)

**Table 1 : Baseline characteristics of trial participants**

	19.84%	15.4% (615)	14.8% (592)	14.9% (600)	15.0% (600)	15.1% (603)	15.8% (633)	15.1% (3,643)
	19.99%	5.3% (211)	5.4% (218)	6.0% (243)	4.8% (193)	4.6% (183)	5.6% (224)	5.3% (1,272)
	20.24%	12.7% (510)	13.2% (527)	13.9% (558)	13.8% (554)	14.6% (584)	13.9% (558)	13.7% (3,291)
	Other	3.4% (135)	5.4% (215)	4.8% (194)	5.6% (224)	5.8% (231)	5.6% (227)	5.1% (1,226)
Credit limit		\$14,416 (± \$9,828)	\$14,500 (± \$10,078)	\$14,393 (± \$9,837)	\$14,431 (± \$9,724)	\$14,424 (± \$9,785)	\$14,355 (± \$9,754)	\$14,420 (± \$9,834)
Pre-trial payments		\$277 (± \$205)	\$279 (± \$209)	\$276 (± \$200)	\$275 (± \$199)	\$279 (± \$206)	\$276 (± \$200)	\$277 (± \$203)
Pre-trial balance		\$11,512 (± \$8,403)	\$11,630 (± \$8,670)	\$11,461 (± \$8,299)	\$11,491 (± \$8,326)	\$11,596 (± \$8,470)	\$11,475 (± \$8,265)	\$11,527 (± \$8,406)

Note: This table shows the characteristics of all individuals enrolled in the trial at randomisation. For characteristics presented as categories, we report raw numbers as well as percentages. Percentages do not always sum to 100% due to rounding error. For continuous characteristics (such as payments/balance) we present means along with standard deviations.

**Table 2 : Baseline characteristics of trial participants by communications channel**

	Email	SMS	Total sample		Email	SMS	Total sample
<i>n</i>	9,462	14,591	24,053	Interest rate			
Age					13.49%	44.1% (6,430)	43.6% (10,485)
45 or less	31.3% (2,961)	28.1% (4,099)	29.4% (7,060)		15.99%	18.3% (2,666)	17.0% (4,100)
> 45	68.7% (6,501)	71.9% (10,492)	70.6% (16,993)		19.84%	14.7% (2,147)	15.1% (3,643)
Sex					19.99%	5.1% (747)	5.3% (1,272)
Female	45.0% (4,259)	44.3% (6,464)	44.6% (10,723)		20.24%	12.6% (1,839)	13.7% (3,291)
Male	55.0% (5,203)	55.7% (8,127)	55.4% (13,330)	Other	2.1% (201)	2.4% (346)	5.1% (1,226)
Card type				Credit limit	\$15,351 (± 10,347)	\$13,818 (± 9,439)	\$14,420 (± \$9,834)

**Table 2 : Baseline characteristics of trial participants by communications channel**

Rewards	19.6% (1,853)	15.9% (2,322)	17.4% (4,175)	Pre-trial payments	\$297 (± 215)	\$264 (± 194)	\$277 (± \$203)
Non-Rewards	77.4% (7,326)	81.4% (11,873)	79.8% (19,199)	Pre-trial balance	\$12,391 (± 8,936)	\$10,967 (± 7,994)	\$11,527 (± \$8,406)
Missing	3.0% (283)	2.7% (396)	2.8% (679)				

Note: This table shows the characteristics of all individuals enrolled in the trial at randomisation. For characteristics presented as categories, we report raw numbers as well as percentages. Percentages do not always sum to 100% due to rounding error. For continuous characteristics (such as payments/balance) we present means along with standard deviations.

**Table 3 : Monthly descriptive statistics for payments and balances in dollars (mean ± SD)**

Period	Control		Short		Loss frame + balance		Loss frame + debt		Social norm + balance		Social norm + debt	
	Payment (\$)	Balance (\$)	Payment (\$)	Balance (\$)	Payment (\$)	Balance (\$)	Payment (\$)	Balance (\$)	Payment (\$)	Balance (\$)	Payment (\$)	Balance (\$)
Jun-17	551 ± 1,759	12,212 ± 8,959	616 ± 2,135	12,365 ± 9,366	605 ± 2,162	12,193 ± 8,938	673 ± 2,109	12,143 ± 8,882	641 ± 2,139	12,372 ± 9,055	608 ± 1,958	12,217 ± 8,873
Jul-17	553 ± 2,133	12,021 ± 9,034	630 ± 2,283	12,105 ± 9,414	590 ± 2,001	11,933 ± 8,986	625 ± 2,000	11,796 ± 9,010	630 ± 2,203	12,101 ± 9,144	569 ± 1,823	11,926 ± 8,956
Aug-17	614 ± 2,143	11,828 ± 9,034	617 ± 2,083	11,850 ± 9,488	583 ± 1,803	11,727 ± 9,052	562 ± 1,781	11,537 ± 9,126	595 ± 2,030	11,829 ± 9,221	606 ± 1,929	11,708 ± 9,028
Sep-17	561 ± 1,979	11,576 ± 9,100	576 ± 2,104	11,599 ± 9,542	594 ± 2,060	11,473 ± 9,149	582 ± 2,005	11,257 ± 9,224	527 ± 1,744	11,539 ± 9,306	594 ± 2,207	11,383 ± 9,098
Oct-17	538 ± 1,884	11,239 ± 9,098	570 ± 2,086	11,348 ± 9,590	583 ± 2,066	11,207 ± 9,205	516 ± 1,790	10,982 ± 9,268	559 ± 1,926	11,286 ± 9,368	578 ± 2,209	11,115 ± 9,176
Nov-17	502 ± 1,678	11,042 ± 9,221	547 ± 1,770	11,100 ± 9,604	544 ± 1,866	10,937 ± 9,266	531 ± 1,802	10,754 ± 9,277	523 ± 1,959	11,056 ± 9,463	572 ± 2,118	10,891 ± 9,179
Dec-17	447 ± 1,402	10,869 ± 9,265	502 ± 2,079	10,837 ± 9,666	499 ± 1,760	10,696 ± 9,290	474 ± 1,556	10,508 ± 9,285	550 ± 2,147	10,831 ± 9,456	457 ± 1,449	10,656 ± 9,201
Jan-18	534 ± 2,291	10,710 ± 9,308	497 ± 1,809	10,591 ± 9,638	485 ± 1,794	10,438 ± 9,275	470 ± 1,578	10,357 ± 9,296	444 ± 1,602	10,516 ± 9,400	512 ± 1,707	10,359 ± 9,122

**Table 3 : Monthly descriptive statistics for payments and balances in dollars (mean  $\pm$  SD)**

Feb-18	468 $\pm$ 1,821	10,464 $\pm$ 9,266	490 $\pm$ 1,942	10,348 $\pm$ 9,664	460 $\pm$ 1,679	10,163 $\pm$ 9,234	443 $\pm$ 1,446	10,112 $\pm$ 9,233	483 $\pm$ 1,736	10,344 $\pm$ 9,428	494 $\pm$ 1,586	10,059 $\pm$ 9,123
Mar-18	495 $\pm$ 1,700	10,225 $\pm$ 9,192	422 $\pm$ 1,462	10,069 $\pm$ 9,631	444 $\pm$ 1,497	9,969 $\pm$ 9,219	471 $\pm$ 1,640	9,962 $\pm$ 9,256	462 $\pm$ 1,574	10,135 $\pm$ 9,396	461 $\pm$ 1,532	9,835 $\pm$ 9,170
Apr-18	475 $\pm$ 1,518	10,053 $\pm$ 9,221	453 $\pm$ 1,507	9,958 $\pm$ 9,678	405 $\pm$ 1,184	9,832 $\pm$ 9,228	490 $\pm$ 1,858	9,804 $\pm$ 9,275	472 $\pm$ 1,834	9,972 $\pm$ 9,389	442 $\pm$ 1,424	9,629 $\pm$ 9,125
May-18	401 $\pm$ 1,263	9,892 $\pm$ 9,270	425 $\pm$ 1,508	9,760 $\pm$ 9,634	440 $\pm$ 1,481	9,736 $\pm$ 9,284	447 $\pm$ 1,411	9,645 $\pm$ 9,247	427 $\pm$ 1,290	9,826 $\pm$ 9,403	413 $\pm$ 1,303	9,501 $\pm$ 9,128

Note: This table presents unadjusted means and standard deviations for payment and balance for each month of the trial.

**Table 4: Main results, June 2017 (month 1)**

	<i>n</i>	Repayments (\$)			Percent of balance repaid (%)			Percent repaying > 4% of balance		
		Mean	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value
SMS and email										
Control	4,001	553			5.7			12.6		
Any message	20,052	628	75 (14 to 136)	0.016	6.2	0.5 (0 to 1.1)	0.05	14.4	1.8 (0.6 to 2.9)	0.002
Email only										
Control	1,574	669			6.1			13.0		
Any message	7,888	653	-16 (-132 to 101)	0.8	6.1	0 (-0.9 to 0.9)	0.97	14.3	1.3 (-0.5 to 3.1)	0.16
SMS only										
Control	2,427	478			5.4			12.3		
Any message	12,164	612	134 (67 to 201)	0.00008	6.2	0.9 (0.2 to 1.6)	0.0098	14.4	2.1 (0.6 to 3.5)	0.005

Note: *n* is the group sample size. Means, proportions, treatment estimates, 95 per cent CIs and p-value are from adjusted linear regression models (see 'Method of Analysis' in the technical appendix). The outcome 'percent repaying > 4% of balance' was pre-registered as a secondary outcome. Effect estimates do not always equal the difference in the reported means due to rounding error.

**Table 5: Individual treatment groups compared to control, June 2017 (month 1), SMS only**

<i>n</i>		Repayments (\$)			Percent of balance repaid (%)			Percent repaying > 4% of balance		
		Mean	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value
Control	2,427	478			5.4			12.3		
Short	2,431	643	165 (59 to 271)	0.002	6.5	1.2 (0.2 to 2.1)	0.013	14.6	2.3 (0.4 to 4.2)	0.019
Loss frame + balance	2,435	606	128 (27 to 228)	0.013	6.0	0.7 (-0.2 to 1.6)	0.143	14.4	2.1 (0.2 to 4.1)	0.027
Loss frame + debt	2,431	611	133 (40 to 226)	0.005	6.4	1.1 (0.2 to 2)	0.019	14.4	2.1 (0.2 to 4.0)	0.030
Social norm + balance	2,431	608	130 (32 to 228)	0.009	6.2	0.8 (-0.1 to 1.7)	0.076	14.1	1.8 (-0.1 to 3.7)	0.063
Social norm + debt	2,436	589	111 (20 to 202)	0.017	6.0	0.6 (-0.3 to 1.5)	0.163	14.3	2 (0.1 to 3.9)	0.037

Note: *n* is the group sample size. Means, proportions, treatment estimates, 95 per cent CIs and p-value are from adjusted linear regression models (see 'Method of Analysis' in the technical appendix). The outcome 'percent repaying > 4% of balance' was pre-registered as a secondary outcome. Effect estimates do not always equal the difference in the reported means due to rounding error.

**Table 6: Individual treatment groups compared to control, June 2017 (month 1), SMS only**

	<i>n</i>	Repayments (\$)			Percent of balance repaid (%)			Percent repaying > 4% of balance		
		Mean	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value
<b>Loss messages vs short message</b>										
Short	2,431	643			6.5			14.6		
Loss frame	4,866	608	-35 (-141 to 71)	0.5	6.2	-0.3 (-1.2 to 0.6)	0.5	14.4	-0.2 (-1.9 to 1.5)	0.8
<b>Social norm messages vs short message</b>										
Short	2,431	645			6.5			14.6		
Social norm	4,867	601	-44 (-149 to 61)	0.4	6.1	-0.4 (-1.3 to 0.4)	0.3	14.2	-0.4 (-2.1 to 1.3)	0.7
<b>Balance messages vs debt messages</b>										
Balance	4,866	606			6.1			14.2		
Debt	4,867	599	-8 (-85 to 70)	0.8	6.2	0.1 (-0.6 to 0.8)	0.7	14.4	0.1 (-1.3 to 1.5)	0.9

Note: *n* is the group sample size. Means, proportions, treatment estimates, 95 per cent CIs and p-value are from adjusted linear regression models (see 'Method of Analysis' in the technical appendix). The outcome 'percent repaying > 4% of balance' was pre-registered as a secondary outcome. Effect estimates do not always equal the difference in the reported means due to rounding error.

**Table 7: Control vs any message comparisons among the SMS group for selected months**

	<i>n</i>	Repayments (\$)			Percent of balance repaid (%)			Percent repaying > 4% of balance		
		Mean	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value	%	Effect (95% CI)	p-value
<b>July (month 2)</b>										
Control	2,427	495			5.7			14.2		
Any message	12,164	573	78 (6 to 150)	0.03	6.5	0.9 (0.2 to 1.6)	0.014	14.3	0.1 (-1.4 to 1.6)	0.9
<b>August (month 3)</b>										
Control	2,427	603			6.4			15.7		
Any message	12,164	568	-35 (-125 to 55)	0.4	7.0	0.6 (-0.2 to 1.4)	0.14	17.1	1.3 (-0.3 to 2.9)	0.1
<b>October (month 5)</b>										
Control	2,427	506			6.6			15.8		
Any message	12,164	529	24 (-53 to 101)	0.55	6.7	0.1 (-0.7 to 0.9)	0.76	16.9	1.1 (-0.5 to 2.7)	0.2

Note: *n* is the group sample size. Means, proportions, treatment estimates, 95 per cent CIs and p-value are from adjusted linear regression models (see Method of Analysis in the technical appendix). The outcome 'percent repaying > 4% of balance' was pre-registered as a secondary outcome. Effect estimates do not always equal the difference in the reported means due to rounding error.

**Table 8 : Balance at six months (October 2017) and twelve months (March 2018)**

<i>n</i>		Balance at six months (\$)			Balance at twelve months (\$)		
		Mean	Effect (95% CI)	p-value	Mean	Effect (95% CI)	p-value
Control	2,427	10,623			9,571		
Any message	12,164	10,374	-249 (-462 to -37)	0.021	9,206	-365 (-635 to -95)	0.008

Note: Exploratory analysis, *n* is the group sample size. Means, proportions, treatment estimates, 95 per cent CIs and p-value are from adjusted linear regression models (see Method of Analysis in the technical appendix). Effect estimates do not always equal the difference in the reported means due to rounding error.

**Table 9 : Effect of SMS messages on repayments by subgroup**

Level		<i>n</i>	Any message / Control difference (95% CI)	p-value	Difference across levels (95%)	p-value
Card type	non-Rewards card	11,873	92 (17 to 168)	0.017		
	Rewards card	2,322	264 (121 to 407)	0.0003	172 (10 to 334)	0.04
Age	45 or less	4,099	111 (-11 to 232)	0.07		

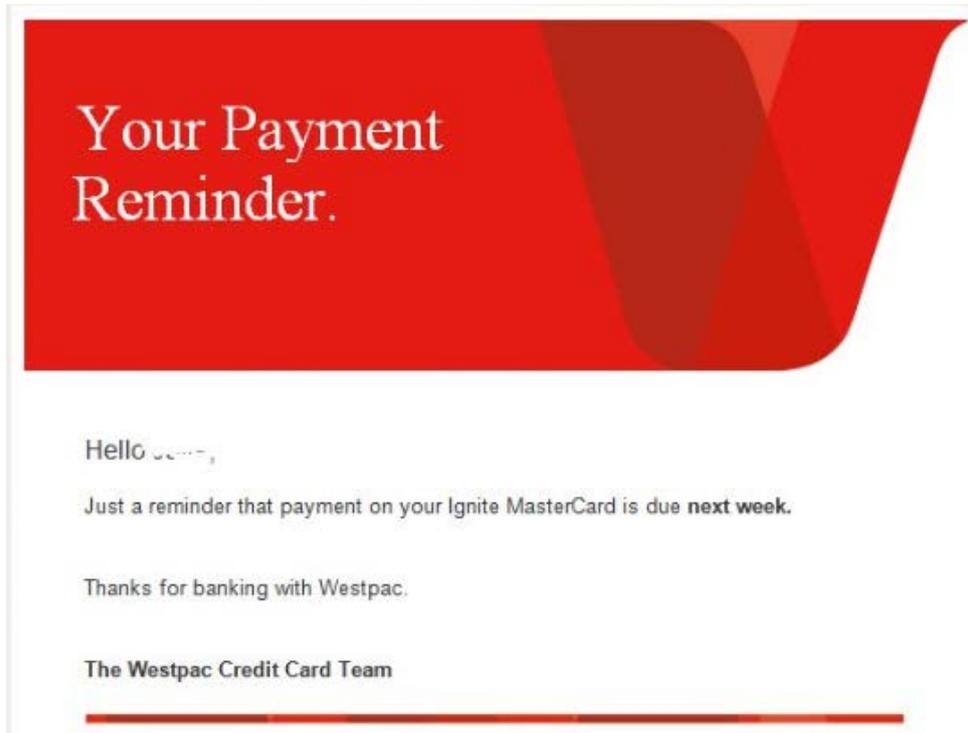
**Table 9 : Effect of SMS messages on repayments by subgroup**

	> 45	10,492	144 (62 to 225)	0.0005	33 (-113 to 179)	0.66
Sex	Female	6,464	129 (57 to 200)	0.0004		
	Male	8,127	137 (29 to 245)	0.013	9 (-121 to 138)	0.9
Credit limit	Lower	6,953	75 (22 to 127)	0.005		
	Higher	7,242	173 (51 to 294)	0.005	98 (-35 to 230)	0.15

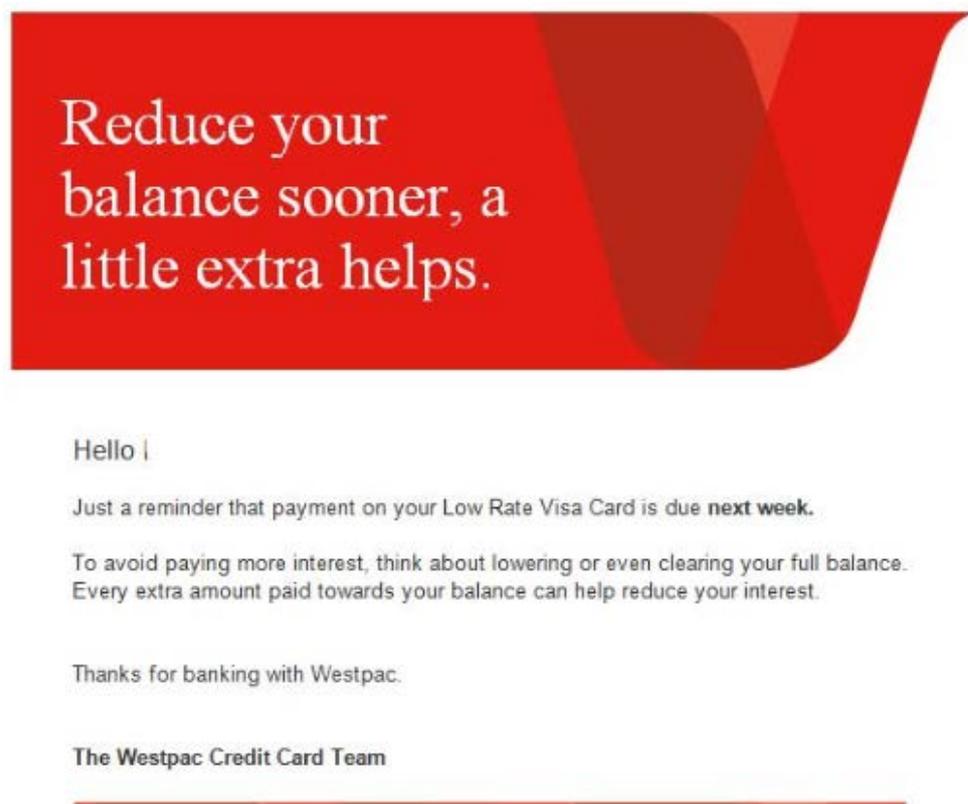
Note: Exploratory analysis, *n* is the group sample size. Means, proportions, treatment estimates, 95 per cent CIs and p-value are from adjusted linear regression models (see Method of Analysis in the technical appendix). The difference across levels was tested by interacting a subgroup indicator with an indicator for treatment (See 'Subgroup Analysis' in the technical appendix for more details). Effect estimates do not always equal the difference in the reported means due to rounding error.

## Appendix C: Email intervention designs

### Attention control: no behavioural elements



### Loss-framed + balance



**Attention control: no behavioural elements  
Loss-framed + debt**

Reduce your debt  
sooner, a little extra  
helps.

Hello Troy,

Just a reminder that payment on your Low Rate Visa Card is due **next week**.

To avoid paying more interest, think about lowering or even clearing your full debt. Every extra amount paid towards your debt can help reduce your interest.

Thanks for banking with Westpac.

**The Westpac Credit Card Team**

**Social norm + balance**

Reduce your  
balance sooner, a  
little extra helps.

Hello Troy,

Just a reminder that payment on your 55 Day Platinum Visa Card is due **next week**.

Many people choose to pay the full balance on time. Every extra amount paid towards your balance can help reduce your interest.

Thanks for banking with Westpac.

**The Westpac Credit Card Team**

**Attention control: no behavioural elements  
Social norm + debt**



Hello

Just a reminder that payment on your Low Rate Visa Card is due **next week**.

Many people choose to pay the full debt on time. Every extra amount paid towards your debt can help reduce your interest.

Thanks for banking with Westpac.

**The Westpac Credit Card Team**

---

# References

---

Adams, P., Guttman-Kenney, B., Hayes, L. and Hunt, S. 2018. *Helping credit card users repay their debt: a summary of experimental research*. London: Financial Conduct Authority.

Agarwal, S., Chomsisengphet, S., Mahoney, N. and Stroebel, J., 2014. Regulating consumer financial products: Evidence from credit cards. *The Quarterly Journal of Economics*, 130(1), pp.111-164.

Australian Banking Association 2018, *Australians becoming smarter with their cards as debt falls*, 23 January, Accessed 06/02/2018, Available at: <https://www.ausbanking.org.au/media/media-releases/media-release-2018/australians-becoming-smarter-with-their-cards-as-debt-falls>.

The Australian Government the Treasury 2016, *Credit cards: improving consumer outcomes and enhancing competition*.

Australian Securities & Investments Commission, 2018. *REP 580 Credit card lending in Australia*.

Doyle, Mary-Alice., 2018. *Consumer Credit Card Choice: Costs, Benefits and Behavioural Biases*. Canberra: Reserve Bank of Australia, Research Discussion Paper – RDP 2018-11.

Heidhues, P. and Köszegi, B., 2010. Exploiting naivete about self-control in the credit market. *American Economic Review*, 100(5), pp.2279-2303.

Jones, L.E., Loibl, C. and Tennyson, S., 2015. Effects of informational nudges on consumer debt repayment behaviors. *Journal of Economic Psychology*, 51, pp.16-33.

Keys, B.J. and Wang, J., 2019. Minimum payments and debt paydown in consumer credit cards. *Journal of Financial Economics*.

Lin, W., 2013. Agnostic notes on regression adjustments to experimental data: Reexamining Freedman's critique. *The Annals of Applied Statistics*, 7(1), pp.295-318.

*National Consumer Credit Protection Regulations 2010 (NCCP)*

*National Consumer Credit Protection Regulations 2010 (Cth)*, Regulations Reg. 79B.

Navarro-Martinez, D., Salisbury, L.C., Lemon, K.N., Stewart, N., Matthews, W.J. and Harris, A.J., 2011. Minimum required payment and supplemental information disclosure effects on consumer debt repayment decisions. *Journal of Marketing Research*, 48(SPL), pp.S60-S77.

Reserve Bank of Australia (November 2018), *Credit and Charge Card Statistics – C1*, Statistical Tables, Available at: <https://www.rba.gov.au/statistics/tables/xls/c01hist.xls?v=2019-01-18-16-03-31>.

Stewart, N., 2009. The cost of anchoring on credit-card minimum repayments. *Psychological Science*, 20(1), pp.39-41.

Treasury (2016) *Credit Cards: Improving Consumer Outcomes and Enhancing Competition*

Wesley Mission 2015, *The Wesley Report: Facing financial distress*.

Wasserstein, R.L. and Lazar, N.A., 2016. The ASA's statement on p-values: context, process, and purpose. *The American Statistician*, 70(2), pp.129-133.

Yadav, Kabir and Lewis, Roger (2017) 'Gatekeeping strategies for avoiding false-positive results in clinical trials with many comparisons' *JAMA Guide to Statistics and Methods*, 318:14, 1385-1386.

---

## © Commonwealth of Australia 2019

978-1-925364-08-8 Credit where it's due: timely reminders help consumers reduce their credit card debt (online)

### Copyright Notice

With the exception of the Commonwealth Coat of Arms, this work is licensed under a Creative Commons Attribution 4.0 International license (CC BY 4.0). For more information, see the creative commons website at <https://creativecommons.org/licenses/by/4.0/>



### Third party copyright

Wherever a third party holds copyright in this material, the copyright remains with that party. Their permission may be required to use the material. Please contact them directly.

### Attribution

This publication should be attributed as follows:

© Commonwealth of Australia, Department of the Prime Minister and Cabinet, Credit where it's due: timely reminders help consumers reduce their credit card debt

### Use of the Coat of Arms

The terms under which the Coat of Arms can be used are detailed on the following website: <http://www.pmc.gov.au/government/its-honour>



Australian Government

**BETA**

Behavioural Economics Team  
of the Australian Government

General enquiries [beta@pmc.gov.au](mailto:beta@pmc.gov.au)

Media enquiries [media@pmc.gov.au](mailto:media@pmc.gov.au)

Find out more [www.pmc.gov.au/beta](http://www.pmc.gov.au/beta)