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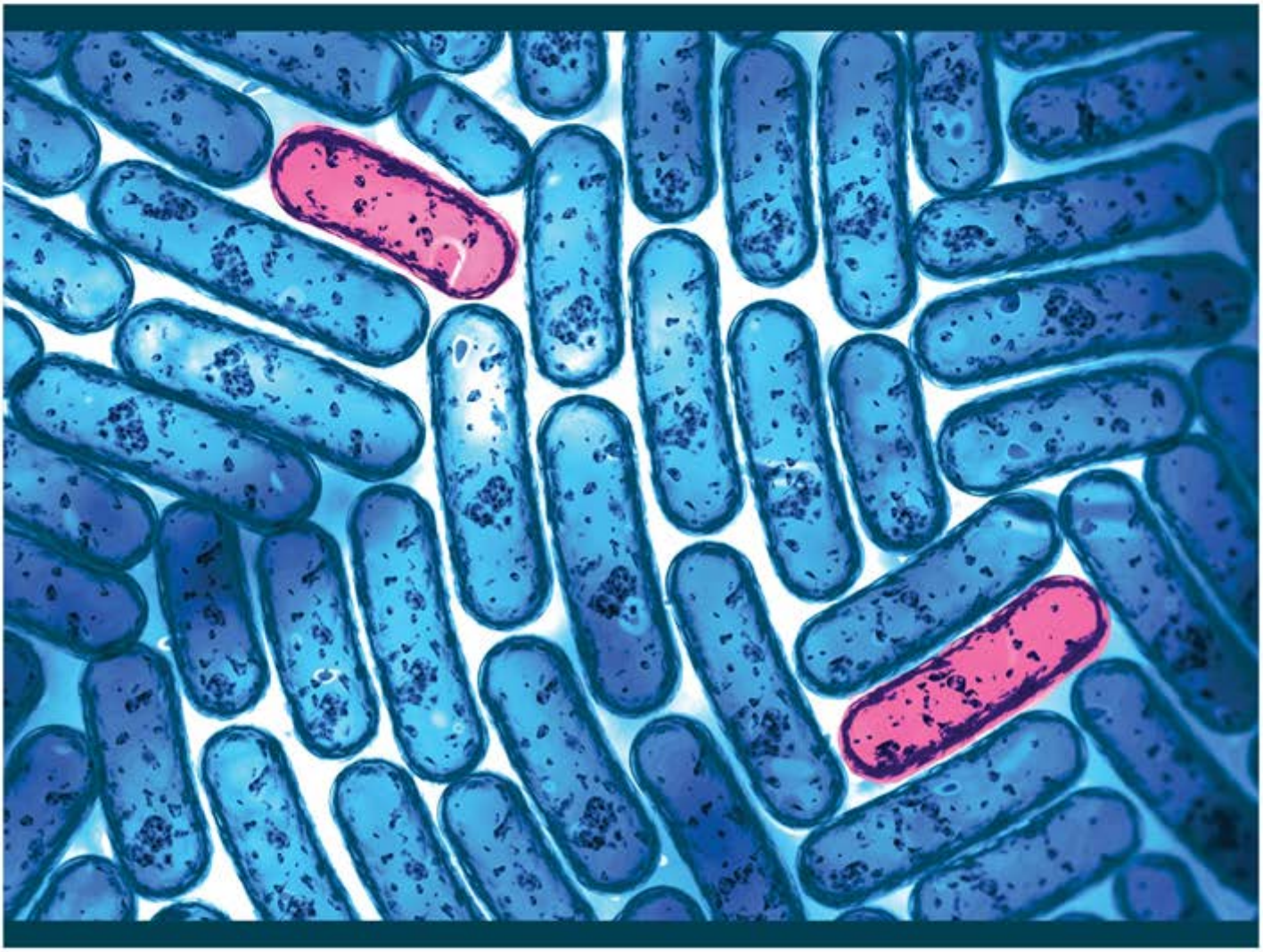

Nudge vs Superbugs

A behavioural economics trial
to reduce the overprescribing of antibiotics

June 2018

BERT Ideas with Evidence Behavioural Economics & Research Team

BETA

978-1-925363-41-8 Nudge vs Superbugs: A behavioural economics trial to reduce the overprescribing of antibiotics (DOCX)

978-1-925363-42-5 Nudge vs Superbugs: A behavioural economics trial to reduce the overprescribing of antibiotics (PDF)

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Project Team

The trial described in this report was a collaborative effort between the Behavioural Economics and Research Team (Department of Health) and the Behavioural Economics Team of the Australian Government (Department of the Prime Minister and Cabinet).

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Acknowledgments

The project team would like to thank Professor Brendan Murphy, Australia's Chief Medical Officer, and Mr Simon Cotterell PSM, First Assistant Secretary of the Provider Benefits Integrity Division. Without their valuable support and assistance this project would not have happened.

Thank you also to:

National Prescribing Service MedicineWise for their assistance, and the use of posters, website material and the Respiratory Tract Infection Action Plan.

The Medical Advisers from Provider Benefits Integrity Division for their advice and assistance, with a special thanks to Dr David Rankin.

Mr Scott Pryor from Provider Benefits Integrity Division's data analytics team.

Our other colleagues in the Department of Health with special thanks to the Office of Health Protection, Health Call Centre staff, and the Technology Assessment and Access Division.

We would also like to acknowledge those organisations we consulted on the project including the Australian Medical Association, Royal Australian College of General Practitioners and the Australian College of Rural and Remote Medicine.

The trial was pre-registered on the BETA website and the American Economic Association registry:

https://www.pmc.gov.au/domestic-policy/behavioural-economics/beta-registered-trials?page=1

https://www.socialscienceregistry.org/trials/2420

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The problem

Antimicrobial resistance (AMR) is one of the biggest threats to human health today. AMR occurs when microorganisms, such as bacteria, become resistant to an antimicrobial medicine, such as antibiotics. Resistant infections are more difficult to treat and, in some cases, untreatable. It can affect anyone, of any age, and in any country.

Australians use a lot of antibiotics and this increases the chance for bacteria to develop resistance to antibiotics.

Within Australia, General Practitioners (GPs) currently prescribe the greatest portion of antibiotics due to the types of illnesses seen and the large volumes of patients. This makes GPs important partners in efforts to minimise AMR by helping limit community prescribing to only those clinical situations where evidence shows antibiotics to be of proven value.

What we did

We applied behavioural insights to design letters sent by the Australian Government's Chief Medical Officer (CMO) to high-prescribing GPs. In particular, we used peer comparison by comparing GPs' prescribing rates with those of other GPs in their region.

We undertook a randomised controlled trial (RCT) involving 6,649 GPs to test the impact of our letters. Just as RCTs are regarded as the 'gold standard' for testing clinical interventions, they are increasingly being used to determine what works in public policy.

As part of our RCT, the CMO wrote to GPs whose prescribing rates were in the top 30 per cent for their region. The letters aimed to prompt GPs to reflect on whether there were opportunities to reduce prescribing where appropriate and safe. The letters were sent on 9 June 2017, just before the rapid increase in prescribing which occurs during the cold and flu season.

GPs received one of four different versions of the letter from the CMO:

- **Education-only** letter containing the usual education messages about AMR, antibiotic prescribing and two National Prescribing Service (NPS) posters.
- **Education with peer comparison** letter including the same education information as the *education-only* letter and a tagline providing the GP with their prescribing rate compared to peers in their region.
- **Peer comparison with graph** letter including the peer comparison tagline along with a visual attention-grabbing graph.
- **Peer comparison with delayed prescribing** letter including the peer comparison tagline with delayed prescribing material (stickers and the NPS's action plan for managing respiratory tract infections).

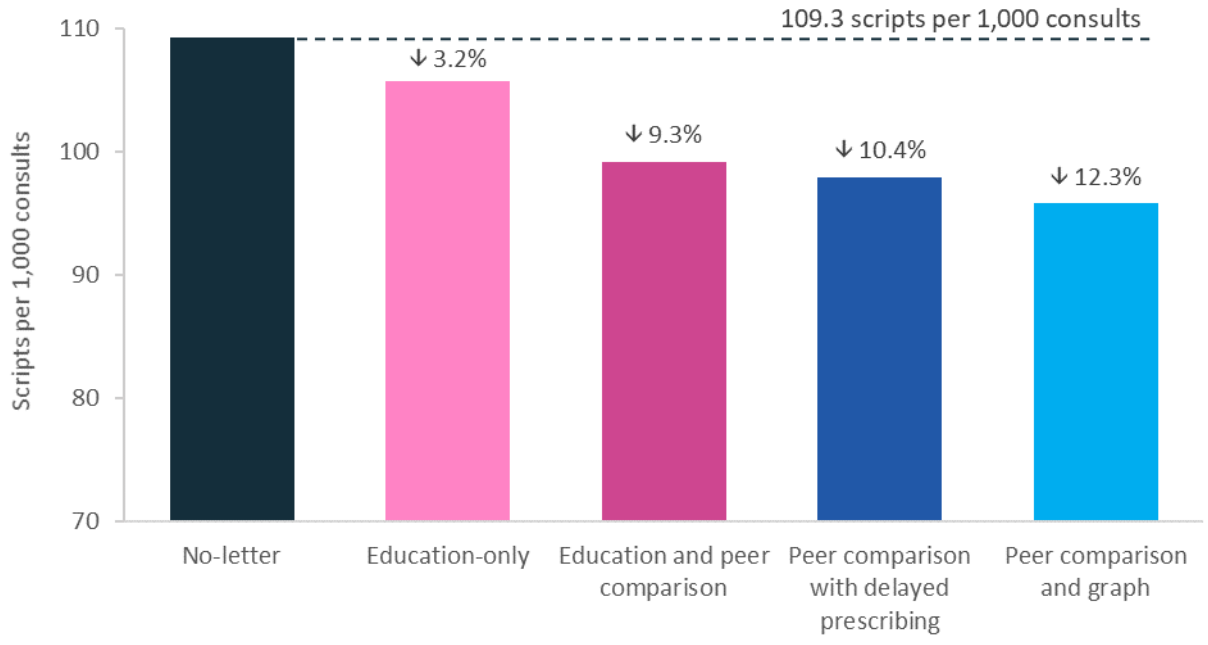
What we found

Overall, we estimate that 126,352 fewer scripts were filled over the six-month period as a result of the letters.

The three letters containing peer comparison information outperformed the education-only letter, and resulted in a substantial reduction in prescription rates. Compared to GPs who did not receive a letter, the peer comparison letters resulted in a 9.3 to 12.3 per cent reduction in prescription rates over six months. In comparison, the *education-only* letter reduced antibiotic prescriptions by 3.2 per cent over six months.

The *peer comparison with graph* performed best. This letter reduced prescription rates by 12.3 per cent over the six-month period, and by 14.6 per cent in the best performing month.

Main findings for six months combined (prescription rates)



Conclusion

The results of our trial demonstrate a peer comparison letter from a respected authority – Australia's CMO – can have large impacts on antibiotic prescribing by Australian GPs. The study also demonstrates letters incorporating peer comparison information outperformed education letters about AMR.

Our findings can help inform future efforts to reduce the risk of AMR caused by the overprescribing of antibiotics. They suggest antibiotic stewardship programs can maximise their effects by using peer comparison feedback to assist doctors to reflect on their prescribing practices.

While our trial focused on the antibiotic prescribing of GPs, our successful results should inspire policy makers to test similar peer comparison interventions and their impacts over time.

Introduction

“Antimicrobial resistance is one of the biggest threats to human health today. It is our joint responsibility to change the way we use antibiotics so that our next generations can continue to benefit from these important medicines.”

Professor Brendan Murphy, Australian Government Chief Medical Officer.

Globally, AMR is recognised as a serious threat to human health. The World Health Organization (WHO) describes AMR as one of the key global health issues facing our generation (WHO, 2018). AMR is increasing at a pace exceeding our capacity to develop new antimicrobial drugs able to target resistant bacteria, very few of which have been brought to market in recent years. If not addressed, there are concerns AMR could take modern medical practice back to the pre-antibiotic era, when simple infections caused significant harm (Department of Health and Department of Agriculture, 2015).

Resistant infections are more difficult to treat and, in some cases, untreatable. AMR can lead to longer hospital stays, higher medical costs and, in some circumstances, death.

The global unrestrained use of antibiotics across human and animal health and agriculture is largely responsible for accelerating the AMR process (Chan, 2011). When we use antibiotics, some bacteria die but resistant bacteria can survive and even multiply. Overuse or inappropriate use of antibiotics makes resistant bacteria more common. The more we use antibiotics, the more bacteria can become resistant.

As AMR continues to grow, Australia is likely to experience clinical situations already seen in other countries where (Department of Health and Department of Agriculture, 2015):

- Routine surgical procedures, such as caesarean sections, become much higher risk.
- Transplant programs have to be halted and Intensive Care Units closed to deal with contamination by highly resistant organisms.
- Pneumonia, gonorrhoea and urinary tract infections become increasingly difficult to treat.
- Medical costs and mortality rates attributable to infection increase.

In June 2015, the Australian Government released the National Antimicrobial Resistance Strategy 2015–2019 (the Strategy)—the first nationally coordinated, multi-sectoral response to AMR in Australia. The Strategy aligns with the WHO's Global Action Plan on Antimicrobial Resistance. It was jointly developed with the Australian Government Departments of Health and Agriculture and Water Resources in consultation with experts and stakeholders from across the human and animal health, food and agriculture sectors (a 'One-Health' approach).

The Strategy recognises that concerted efforts are needed in Australia to reduce the inappropriate use of antibiotics across general practice, hospitals, laboratories, the agricultural industry and the animal health profession.

Australia has a high consumption of antibiotics

In the health setting, the appropriate and judicious use of antibiotics is essential to slowing the emergence of resistance. In this context, the high rate of consumption of antibiotics in Australia is an area of immediate concern. In 2015, Australia's antibiotic prescribing rate of 23.5 Defined Daily Doses (DDDs) per 1000 people was higher than the OECD average (20.6 DDDs per 1000 people per day; OECD, 2017).

GPs are important partners in limiting AMR

Within Australia, GPs currently prescribe the greatest portion of antibiotics due to the large volumes of patients and types of illnesses they see (Department of Health and Department of Agriculture, 2015). This makes GPs important partners in efforts to minimise AMR by helping limit community prescribing to clinical situations where evidence shows antibiotics to be of proven value.

The rate of antimicrobial prescriptions in GP consultations has shown a small decline from 2010 to 2015 (ACSQHC, 2017). Recent research estimates GPs are prescribing antibiotics for acute respiratory infections (ARIs) at rates up to nine times higher than recommended by the Therapeutic Guidelines (McCullough et al., 2017).

This suggests there is scope to reduce antibiotic prescribing in primary healthcare settings without harming access to necessary treatments. Any reduction in prescribing in the primary care setting would likely have significant impact on Australia's overall prescribing rates due to the large portion of antibiotics prescribed by GPs.

Antibiotics don't work for colds, flus and coughs

Antibiotics only work on infections caused by bacteria, not a virus.

Acute respiratory infections (ARIs) are among the most common problems seen by GPs in Australia (Del Mar et al., 2017). An ARI is an infection of the ears, nose, sinuses, throat and/or lungs.

ARIs are caused by viruses, not bacteria. However, in the early stages it can be difficult to determine if an infection is an ARI or the start of a more serious infection.

The common cold and the flu are caused by viruses. This means antibiotics won't make patients feel better or help them recover faster when they have a cold or the flu.

In the past, it was common practice for doctors to prescribe antibiotics for an ARI just in case the primary infection, or a secondary infection, was caused by a bacterial infection. However, today antibiotics are not recommended to be routinely prescribed for many ARIs.

Why do GPs overprescribe antibiotics?

A GP may overprescribe antibiotics for several reasons (Del Mar et al., 2017):

- In the early stages of an ARI, it can be difficult to tell whether an infection is mild or the start of a more serious illness (e.g. pneumonia, meningitis). GPs may prescribe antibiotics to minimise this risk.
- Illnesses like colds and flus are caused by viruses (for which antibiotics don't work) but can cause similar symptoms to bacterial infections.
- GPs can be under time pressure to see a large number of patients and providing an antibiotic script may be a faster way to complete a consultation rather than explain why an antibiotic is unnecessary.
- A GP may perceive refusing to prescribe antibiotics to patients could threaten the doctor-patient relationship, which is an important part of GP practice.

At the same time, the reasons to avoid prescribing antibiotics are not always salient or immediate (Mehrotra & Linder, 2016). The link between prescribing to a patient and its potential impact on AMR is not directly observable or tangible at the time of prescribing. While feedback from the patient and their condition is immediate and visible, AMR is a long-term consequence not yet widely seen in general practice.

A behavioural economics approach

We developed four letters for the CMO to send to high-prescribing GPs to prompt them to reflect on whether there were opportunities to reduce prescribing where appropriate and safe. We applied insights from behavioural economics in the design of the letters. This section describes the relevant behavioural insights and gives an overview of how we applied them to the design of the letters.

What is behavioural economics?

Behavioural economics examines how people make decisions, taking into account critical insights from psychology about the social, cognitive and emotional aspects of people's choices. It recognises people's judgements are systematically biased and limited. For example, we often forget things or overlook important details, and make decisions conflicting with our own interests, such as by giving in to immediate temptations rather than doing the things which are best for us in the long term.

Why is behavioural economics useful?

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 economics applies behavioural insights to the real world by drawing on empirically-tested results. These 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 design policies that go with the grain of human behaviour. For example, citizens may struggle to act in a way that aligns with their own best interests, such as saving more money in case of an emergency. Policy makers can apply behavioural insights that preserve freedom, but help people align actions with intentions – for example by helping citizens to set a plan to save regularly.

Peer comparison feedback

GPs may have concerns about AMR and its effects but don't necessarily know how their prescribing rates compare to other GPs. This makes it more difficult for GPs to reflect on whether their prescribing behaviours are appropriate.

Peer comparison feedback provides information to individuals on how their own behaviour compares to their peers (see box). It is based on the innate human tendency to look to others to guide how we should act. Effective peer comparison feedback is often targeted at informing outliers their behaviour is above or below the average of their peers. This comparison can motivate individuals to change their behaviour to be closer to the average – that is, to adjust their behaviour towards what is "normal" for their peer group.

The Effects of Peer Comparison

Behavioural science offers many examples of the effectiveness of peer comparison information in leading to behaviour change:

People with overdue tax returns were prompted to lodge their return using peer comparison letters ("Nine out of ten people pay their tax on time"). Recipients of these letters were nearly four times more likely to pay their tax (see Halpern & Gallagher, 2015).

In the United States (US), an electricity company (OPOWER) used peer comparison messages to compare a person's electricity usage to their neighbours'. As a result, estimated electricity consumption was reduced by 2 per cent (see Allcott, 2011).

A sign hung in a hotel room stating 75% of guests re-use their towels more than once increased the amount of towel re-use by 7% (see Goldstein, Cialdini & Griskevicius, 2008).

Messages incorporating peer comparison information about the high proportion of patients who attend medical appointments on time led to a 32% reduction in no-shows (see Martin, Bassi & Dunbar-Rees, 2012).

A US-based study providing first-year intercollegiate athletes with personalised peer comparison feedback substantially reduced heavy drinking among the treatment group, while the control group saw an increase in heavy drinking (see Doumas, Haustveit & Coll, 2010).

Recently, peer comparison feedback was used successfully in a large RCT to reduce antibiotic prescribing rates amongst GPs in the United Kingdom (UK; Hallsworth et al., 2016). The UK's CMO wrote to GPs belonging to 1,581 group practices whose antibiotic prescribing rate was in the top 20 per cent for their local area. The letter informed GPs their practice was prescribing antibiotics at a rate higher than 80 per cent of other practices in their local area. Compared to a control group, the practices whose GPs received the CMO's letters reduced prescribing by 3.3 per cent over a six-month period.

Individual versus group feedback

An important aspect of the design of letters for this trial was considering whether to provide feedback based on individual or group behaviour. The UK study focused on the behaviour of GP practices (that is, groups of GPs) rather than individuals. While individual GPs received a letter, the feedback provided was about how they and their colleagues, as a group, were prescribing. GPs needed to work collectively to reduce the prescribing of their group practice despite antibiotic prescribing being an individual action.

When operating in a group, social psychologists suggest the feelings of responsibility for achieving outcomes can be diffused across group members. In other words, people can "hide in the crowd" (Latane, Williams & Harkins, 1979). When receiving group prescribing information, a GP may believe other GPs in the practice are responsible for the high-prescribing levels because each individual's contribution remains unclear. The GP may also be uncertain about how much to reduce their prescribing – if at all. As a result, the practice's overall prescribing rate may not reduce as much as expected.

To reduce the effect of hiding in a group it is recommended individual contributions are identified and measured against a standard (Karau & Williams, 1993). Targeting feedback at individual GPs rather than groups of GPs provides a potential way to increase individual accountability and the effectiveness of a peer comparison intervention.

Overview of our approach

We designed and tested the impact of four different letters (and associated materials) on the subsequent antibiotic prescribing rates of Australian GPs.

There were five distinctive features of our letter designs.

1. Peer comparison with individual and personalised feedback

We personalised the GPs' feedback by providing individual prescribing rates relative to other GPs in their region (e.g. "You prescribe more antibiotics than 85 per cent of prescribers in the ACT region"). We also gave their actual percentile (e.g. 74th, 91th or 89th percentile). Another recent study seeking to reduce overprescribing of antibiotics used individual peer comparisons, although it differed from our study in other respects (Meeker et al. 2016; see conclusion for further discussion).

2. Targeting the top 30 per cent

We targeted GPs across Australia whose antibiotic prescribing rates were in the top 30 per cent of their geographic region. We wanted to test whether the power of peer comparison information would vary depending on a person's position relative to the average. For example, whether peer comparison would work less effectively for those at the 70th percentile compared to the 90th percentile.

3. More than one letter

We compared four different letters and associated materials to see if one approach had a greater impact on prescribing rates:

- *Education-only* letter – contained standard information about AMR and two National Prescribing Service (NPS) posters.
- *Education with peer comparison letter* – the same as the education-only letter but with a tagline providing the GP with information about their percentile prescribing rate compared to their peers in their region.
- *Peer comparison with graph letter* – included the tagline comparing the GP to their peers along with a visual, attention grabbing graph to make the comparison more salient.
- *Peer comparison with delayed prescribing letter* – included the same tagline comparing the GP to their peers with additional material for wait-and-see prescribing (i.e. delayed prescribing stickers and the NPS's action plan for managing respiratory tract infections).

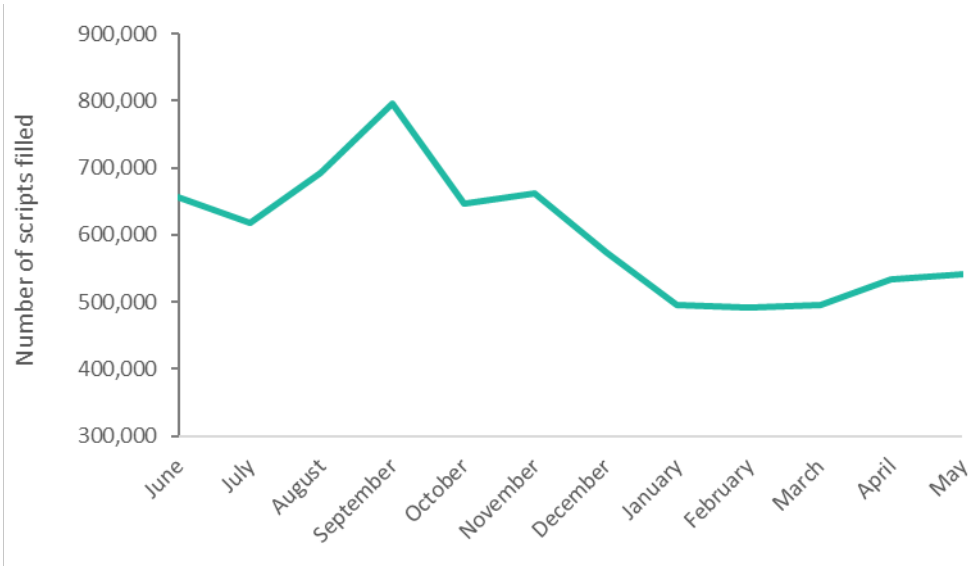
4. The messenger effect

People are influenced by who is communicating with them. Messages from trusted, high profile individuals increase the credibility of the message (Pornpitakpan, 2006). In our trial, we attempted to utilise this messenger effect by having all four letters sent from Australia's CMO.

5. Timing

Antibiotic prescriptions increase during the winter months, due to the cold and flu season. While antibiotics do not work for colds and flus, more people get sick with both viral and bacterial infections in the winter months and more antibiotics are prescribed. The letters were sent on 9 June 2017 to coincide with this yearly spike in antibiotic use.

Figure 1: Antibiotic prescriptions are higher during the cold and flu season



Antibiotic prescriptions are usually highest between June and November, due to the cold and flu season. This graph presents monthly prescription data for 22,305 GPs from June 2016 to May 2017.

What we did

We designed four letters to prompt high-prescribing GPs to reflect on whether there were opportunities to reduce prescribing where appropriate and safe. Three letters made use of peer group comparisons, while the fourth was presented in the format of an education campaign.

Initially, we designed several draft letters using behavioural economic concepts, academic literature and material from the NPS. We then tested and refined the letters through consultation with internal stakeholders in the Department of Health, including focus groups with medical advisers in the Provider Benefits Integrity Division (PBID) (who work as GPs part-time within a practice).

Once the letters were finalised, the CMO provided them to the Australian Medical Association (AMA), Royal Australian College of General Practitioners (RACGP) and the Australian College of Rural and Remote Medicine (ACRRM) for their input and comment.

This section describes the design of the four letters and how we tested them using an RCT.

Education-only letter

Does reminding GPs about what they already know about AMR influence their behaviour - perhaps by ensuring the issue stays front of mind?

Education campaigns involving marketing materials like posters and leaflets are a common approach to addressing inappropriate prescribing of antibiotics. However, GPs are highly trained professionals who have good knowledge of AMR and how to prescribe antibiotics appropriately. We were interested in knowing if reminding GPs about AMR and appropriate prescribing could influence their behaviour, perhaps by keeping the issue front-of-mind when they are issuing scripts.

The *education-only group* letter was designed to be a typical letter which might have been sent as part of a large education campaign. The letter described the growing threat of AMR and how GPs can help by prescribing appropriately. Attached to the letter were two posters from the NPS used in a previous AMR campaign. One was intended for patients and the other for GPs. The posters outlined what patients and doctors can do to reduce the overprescribing of antibiotics, which the doctors could place in a prominent place in their practice.

Peer comparison letters

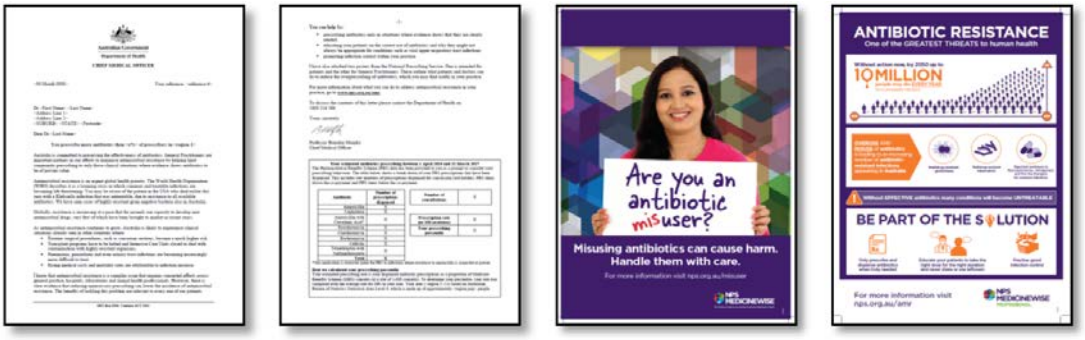
Does targeting feedback at individuals lead to a greater behavioural response than targeting at groups?

In our trial, we were interested to see what would happen if we targeted feedback on antibiotic prescribing at the individual GP level. We used the following tagline:

You prescribe more antibiotics than [X]% of prescribers in the [local region].

The tagline was personalised by providing each GP with their percentile ranking (between 70 per cent and 100 per cent). We expected this personalised feedback would have a larger impact on subsequent prescribing rates than if feedback was targeted at groups of GPs.

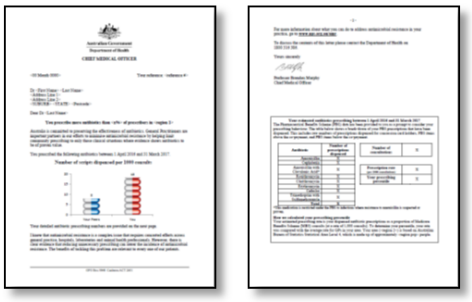
a. Education with peer comparison information



What is the effect of adding peer comparison information to an education letter?

The *education with peer comparison* information group was sent the same letter as the education-only letter group (see above) but we added the comparison tagline to the beginning of the letter. This enabled us to see what the impact of adding peer comparison feedback would have on an education message.

b. Peer comparison with graph



Can the impact of a shorter letter be as powerful as a longer one?

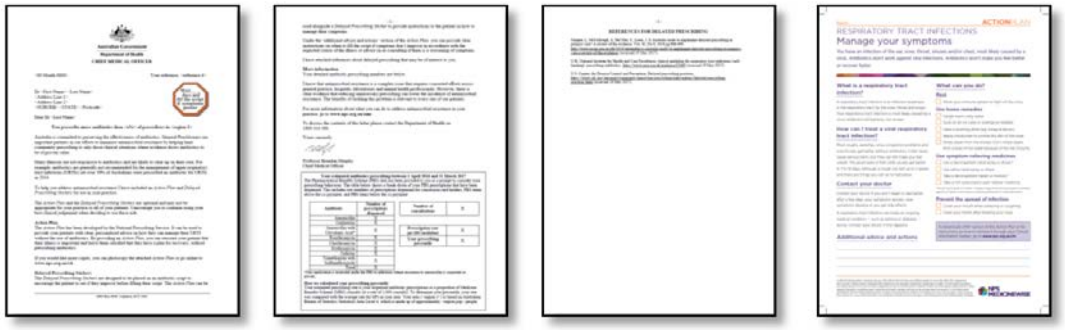
Our attention is limited (Halpern et al., 2010). We are exposed to too much information on a daily basis for us to process it all. Instead, we focus our limited attention on information which appears more salient or relevant to us than other stimuli. Our capacity to recognise important information can, however, be reduced when we have much to think about or are exposed to lots of information.

People are more likely to act on information that attracts their attention. GPs receive large amounts of mail and an education letter may not be salient enough to stand out from other correspondence. Furthermore, as GPs are already well informed about AMR, the education message may not hold their attention because it is not new but simply a reminder of something they already know.

We were interested in seeing if we could increase the saliency of a letter by using a strong visual cue. In addition, we wondered if a shorter letter would be as effective as a longer education letter.

The *peer comparison with graph* group received a short letter which included the peer comparison tagline along with a coloured graph showing how the GP's prescribing compared to their peers. The graph was designed to attract attention and visually emphasised how the GP's prescribing was higher than his or her peers. We made the letter shorter, more direct and with less educational focus.

c. Peer comparison information with delayed prescribing



Does providing GPs with a patient-focused strategy improve the effects of peer comparison information?

GPs have reported one reason for prescribing antibiotics is to meet patient expectations (Fletcher-Lartey, 2016; Sargent et al., 2016). GPs may feel pressured to prescribe antibiotics as patients expect to receive something to resolve their illness. GPs also report educating patients their illness doesn't require an antibiotic is often time-consuming and difficult. It can be quicker and easier to write a script.

We were interested in seeing whether we could improve the effect of the *peer comparison* tagline by providing GPs with a strategy they could implement with their patients. Delayed prescribing is a method in which the GP provides an antibiotic script but asks the patient to wait and see if they improve before filling the script (Sargent et al., 2016). This approach can help meet patients' expectations by providing them with a script. At the same time, research has shown delayed prescribing is an effective strategy for reducing antibiotic use, including for ARIs for which antibiotics offer little to no benefit
(Sargent et al., 2016).

The *peer comparison with delayed prescribing* letter included the peer comparison tagline along with a suggestion to use the delayed prescribing approach. To assist in its implementation, GPs were provided with delayed prescribing stickers which could be placed on an antibiotic script to encourage the patient to wait and see if they improved before filling it. The letter also included the *Respiratory Tract Infection Action Plan* that was developed by the NPS and could be used to provide patients with clear, personalised advice on how to manage symptoms without antibiotics.

How we tested the letters

We ran a cluster RCT to test the effectiveness of the letters. The trial involved five experimental arms: the four different letters, and a control group that received no letter. The trial was clustered by clinic, that is, all high-prescribing GPs within the same clinic were allocated to the same experimental group. For more information on how RCTs work, see box.

What is a randomised controlled trial?

Well-designed 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.

The trial aimed to prompt high-prescribing GPs to reduce prescribing where appropriate and safe. A secondary aim was to test whether peer comparison information led to higher reductions in prescribing rates compared to the standard educational letters.

We compared the prescription rates for each group and hypothesised that:

- GPs in the treatment groups would have lower prescription rates subsequently than GPs in the control group; and
- GPs who received a letter with peer comparison information showing how far above average they were in terms of prescribing would have lower prescription rates than GPs who received an education-only letter.

On 9 June 2017, the letters were sent to GPs across Australia whose antibiotic prescribing rates were in the top 30 per cent for their geographic region. In total, there were 6,649 doctors included in the trial. Of those, 5,311 received a letter and 1,338 did not (the control group).

The 6,649 doctors were grouped by clinic and randomly allocated into the five groups listed (see Table 1).

Table 1: Sample size – number of GPs in each experimental group

Experimental groups	Number of GPs
Control group (no-letter)	1,338
Education-only	1,319
Education with peer comparison	1,311
Peer comparison with delayed prescribing	1,348
Peer comparison with graph	1,333
Total	6,649

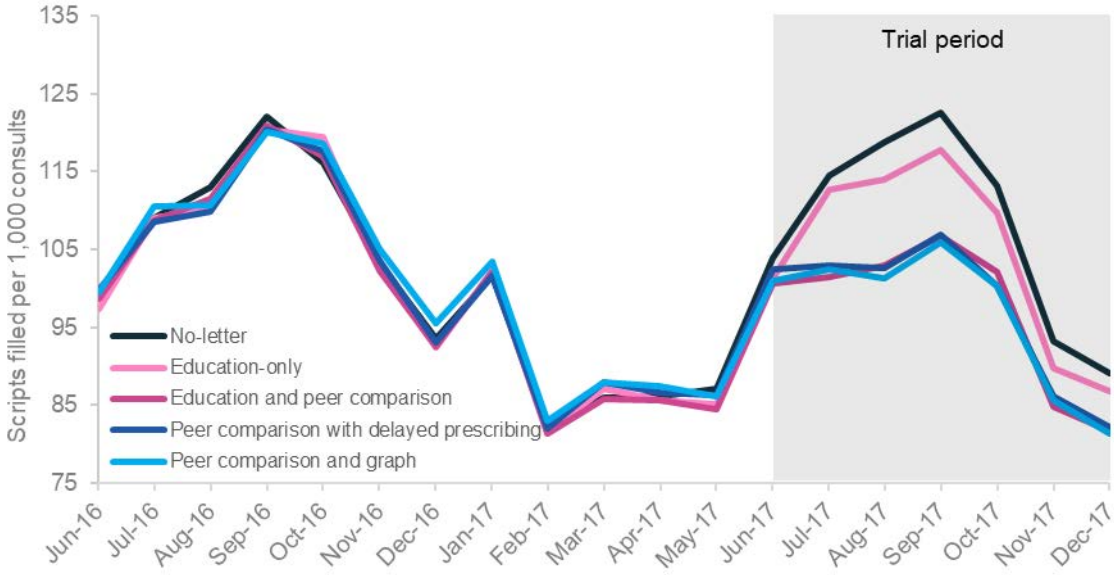
More details on the trial design and a full list of exclusion criteria can be found in **Appendix A**.

Results

Letters containing peer comparison information substantially reduced prescription rates in the six months after the letters were sent. Compared to the no-letter (control) group, the best performing letter reduced prescribing rates by 12.3 per cent.

We begin by comparing the prescription rate – the number of scripts filled per 1,000 consults – in our five groups over time. In the year before the letters were sent, the prescription rates for the five groups were almost identical. Letters were sent on 9 June 2017; after this, there is a striking reduction in the prescription rate in the three peer comparison groups (see **Figure 2**).[1]

Figure 2: Prescription rates among GPs in the trial from June 2016 to December 2017



[1] Note that monthly counts begin on 9 June 2017, when the letters were sent. For example, month 1 after the intervention captures data from 9 June to 8 July.

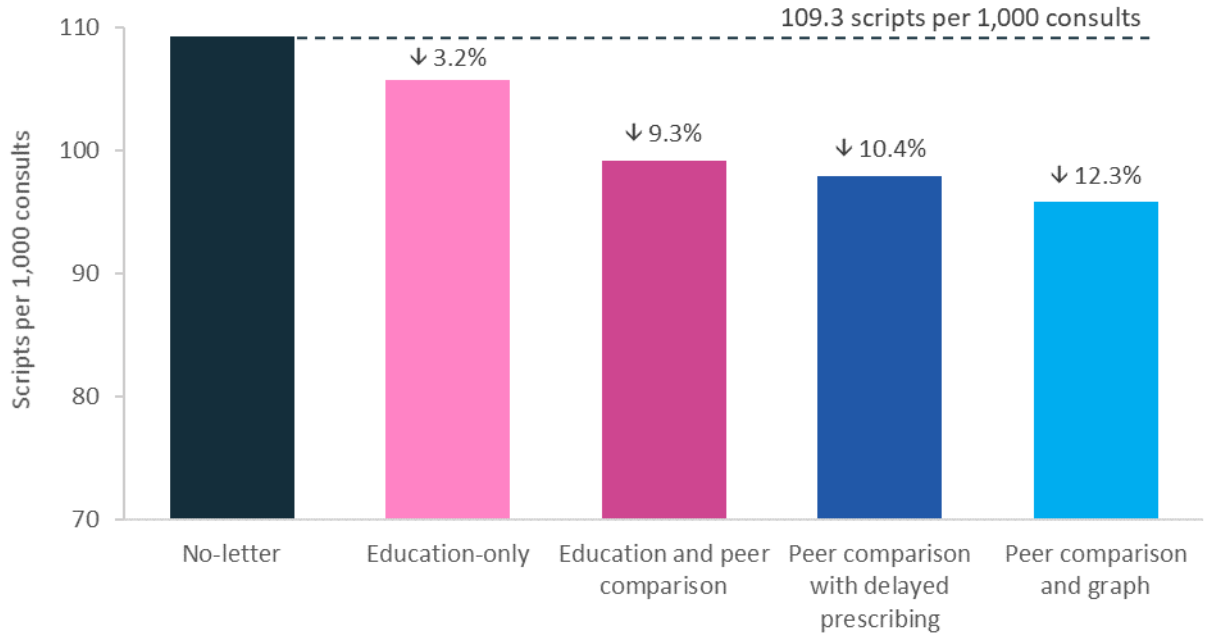
To summarise the impact of our letters, we combined rates for the six-month period after our letters were sent. Over this time, the rate in our no-letter group was 109.3 scripts per 1,000 consults.

The three peer comparison letters caused a 9.3–12.3 per cent reduction in prescribing rates. The best performing letter was the *peer comparison with graph* letter, reducing prescription rates by 12.3 per cent (to 95.8 scripts per 1,000 consults). The *peer comparison with delayed prescribing* letter reduced prescription rates by 10.4 per cent (to 97.9 scripts per 1,000 consults) and the *education with peer comparison* letter reduced rates by 9.3 per cent (to 99.2 scripts per 1,000 consults).

Sending doctors the *education-only* letter cut prescriptions by a modest but statistically significant 3.2 per cent (to 105.8 scripts per 1,000 consults).[2]

Differences between the three peer comparison letters, and the no-letter and education-only groups were statistically significant ($p < 0.0001$ for all comparisons). The combination of large differences and a large sample gives us considerable confidence in these results.

Figure 3: Main findings for six months combined (prescription rates)



Estimates are adjusted means. Bars represent the number of scripts per 1,000 consults and bar labels represent the percentage decreases compared to the no-letter group. See Appendix B for a table of estimates, p-values and confidence intervals.

[2] We are aware, however, there is a lively academic debate about the merits of testing for 'statistical significance', the appropriateness of conventional thresholds such as $p<0.05$ (or any thresholds at all), and even the use of p-values generally. See, in particular, the 'The American Statistical Association Statement on Statistical Significance and P-Values' (Wasserstein and Lazar, 2016).

Effect of the letters by month

Looking at prescription rates for each month (**Figure 4** and **Table 2**), the impact of our three behaviourally-informed letters increased until September (three months after the letters were sent). At its peak, the *peer comparison with graph* letter reduced filled scripts by 14.6 per cent (or 17.3 scripts per 1,000 consults). After this, the difference between the *no-letter* group and the three peer comparison groups began to narrow.

At the end of the six-month period, our three behaviourally-informed letters continued to have an impact, with statistically significant reductions ranging from 7.3 per cent to 8.8 per cent (or 6.5 to 7.8 scripts per 1,000 consults). In contrast, the impact of the *education-only* letter was small and was not always statistically significant at the conventional threshold.

Figure 4: Monthly results of each letter (prescription rates)

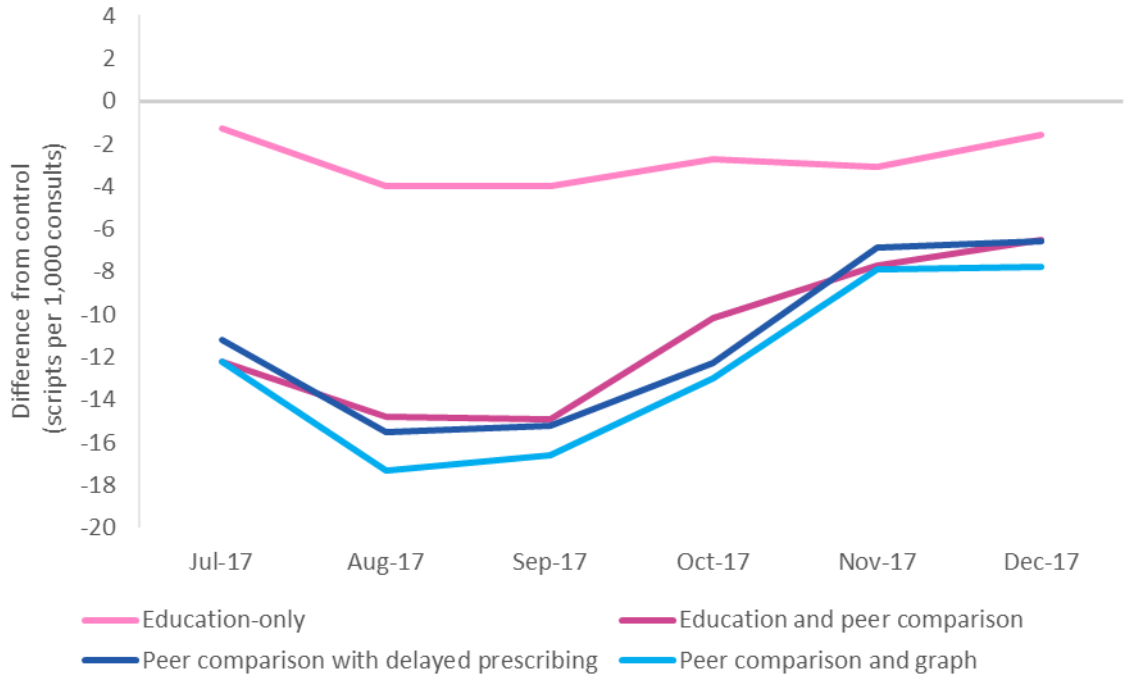


Table 2: Monthly percent change compared to no-letter control group

	Education-only	Education with peer comparison	Peer comparison with delayed prescribing	Peer comparison with graph
July (month 1)	-1.2%	-10.7%	-9.8%	-10.6%
August (month 2)	-3.4%	-12.6%	-13.1%	-14.6%
September (month 3)	-3.4%	-12.2%	-12.4%	-13.6%
October (month 4)	-2.4%	-9.0%	-10.9%	-11.5%
November (month 5)	-3.3%	-8.3%	-7.4%	-8.5%
December (month 6)	-1.8%	-7.3%	-7.4%	-8.8%

See Appendix B, Table 5 for a full table of estimates, confidence intervals and p-values

Impact on the total number of scripts filled

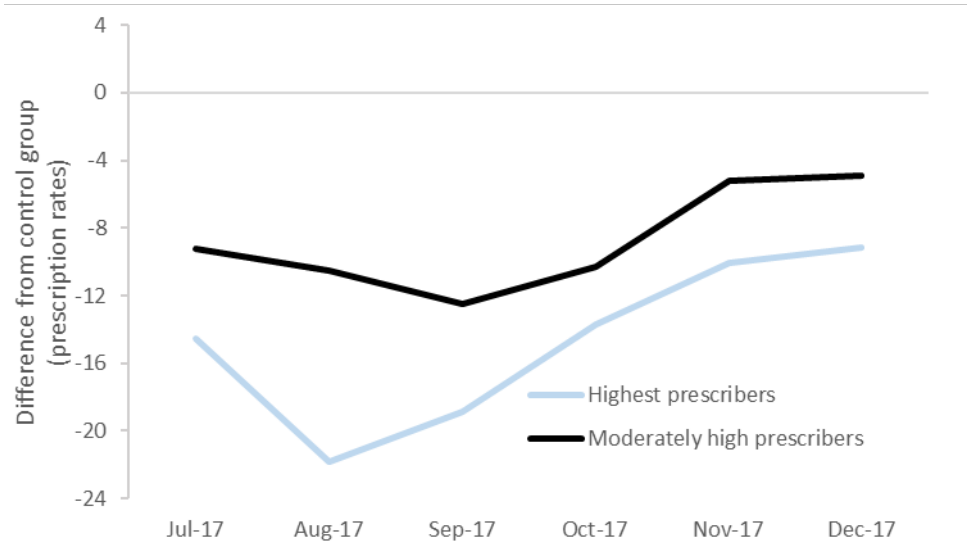
All up, we estimate our four letters reduced the number of scripts being filled by 126,352 over the six-month period after letters were sent compared to the prescribing pattern of GPs who did not receive a letter. If we had sent our best performing letter to all five groups (including the control group) we estimate we could have prevented a total of 208,510 prescriptions.

Highest versus moderately high prescribers

We examined whether our peer comparison letters worked better among the highest prescribers (ranked between the 85th and 100th prescribing percentile) compared to moderately high prescribers (those ranked between the 70th and 85th percentile).

Although there were strong reductions in prescription rates for both groups, our letters were consistently more effective in reducing rates among the highest prescribers. The largest monthly decrease in prescription rates among the highest prescribers was 16.0 per cent (or 21.9 prescriptions per 1,000 consults) in August 2017. In contrast, the highest monthly decrease for the moderately high prescribers was 11.7 per cent (or 12.5 prescriptions per 1,000 consults) in September 2017.

Figure 5: Effect of three peer comparison letters on the highest vs. moderately high prescribers



Estimates are from an adjusted linear regression model. See Appendix B for a table of estimates, p-values and confidence intervals

Secondary analyses

We examined whether doctors with certain characteristics responded differently to our letters. These results should be treated as exploratory as our trial was not explicitly designed to detect effects in subgroups.

The socioeconomic status of the area in which the GPs' clinic was located seemed related to the effect of our letters. Among GPs in the control group, prescription rates were higher in areas with relatively low socioeconomic status compared to areas with relatively high socioeconomic status (112.4 vs 106.5 scripts per 1,000 consults). Those in relatively low socioeconomic areas responded with a greater reduction in prescribing rates (13.6 per cent or 15.3 scripts per 1,000 consults reduction) compared to prescribers in relatively high socioeconomic areas (7.7 per cent or 8.3 scripts reduction).

We found no evidence the effect of the letters differed between GPs of different age or sex (see **Appendix B, Table 9**).

Finally, we looked at weekly data to explore how long it took to see an initial reduction in GPs' prescribing rates after the letters were sent. This would indicate how quickly GPs processed and implemented changes in prescribing habits. In the first week after the letters were sent, the peer comparison letters all led to large reductions in prescribing rates compared to the control group. In contrast, there was only a very small relative decrease resulting from the education-only letter.

Limitations

On 17 June 2017, our trial generated national media coverage across newspapers, television and blogs. We intended the trial to be conducted without media coverage to evaluate the impact of the letters by themselves. In hindsight, media attention was inevitable with a nation-wide intervention on a topical issue.

The media coverage mentioned the CMO was targeting high prescribers (however, the media coverage did not refer to different versions of the letter). This raises the possibility GPs may have altered their behaviour if they thought their prescribing rates were being observed. We expect this may have caused a small reduction in prescribing rates across GPs in the trial, but would have minimal impact on our results. There is also the possibility the media interacted with our interventions in some way to make the interventions more or less effective. Although this may impact generalisability to some extent, it does not affect the internal validity of the trial and we consider our results to be robust. This is especially the case given our trial included the entire population of high-prescribing GPs in Australia.

We recognise it is not possible to determine which GPs actually received and read the letter. Thus our analysis includes all GPs who were sent a letter regardless of what happened after the letter was sent, such as if we received a return-to-sender (this is called 'intent-to-treat' analysis). As such, we are unable to measure how successful the letter was in reaching GPs and whether outcomes could have been increased if delivery was improved. This is the case in any mail-out campaign so we consider we are capturing the real-word effect of our letters.

The outcome for our trial was scripts filled rather than scripts dispensed to the patient. Scripts needed to be taken to a pharmacy and the medication purchased to be counted in the results. We think this is the appropriate outcome indicator, as one strategy doctors may use to lower the number of scripts filled is to ask patients to hold on a few days before filling the script (delayed prescribing).

It is not possible to separate the effects of all the strategies used in each letter. For example, we can't determine if the *education-only* letter's effect was due to the CMO signing the letter or the educational materials included. Similarly, we are unable to determine the effects of the delayed prescribing materials alone without the peer comparison tagline included in the letter.

Finally, we excluded a small number of extreme outliers from our final dataset. **Appendix A** has more information on this.

Discussion and conclusion

AMR is a serious threat to human health and concerted efforts are needed in Australia to reduce the unnecessary prescribing of antibiotics. Our trial shows peer comparison letters from Australia's CMO can successfully reduce the number of antibiotic scripts prescribed by Australian GPs.

Overall, we estimated that our trial prevented 126,352 scripts being filled over six months. If we had sent our best performing letter to all five groups (including the control group) we estimate we could have prevented approximately 208,510 prescriptions over six months.

Education letters addressed from Australia's CMO reduced prescription rates by 3.2 per cent. This is a small, but important, reduction. It suggests that the CMO writing to GPs to inform them about the risk of AMR is enough to modestly reduce antibiotic prescriptions.

Importantly, we found just adding a peer comparison tagline to the education letter almost tripled its effectiveness, reducing prescriptions by 9.3 per cent. This is an impressive improvement considering how simple and inexpensive the change was.

The *peer comparison with graph* letter led to a reduction of 12.3 per cent, which outperformed the *education with peer comparison* letter. While not quite statistically significant at the conventional threshold, this letter also outperformed the others at every time point and would be the letter of choice for future interventions.

The *peer comparison with delayed prescribing* letter reduced prescribing rates by 10.4 per cent, which is not statistically different from the other peer comparison letters. This indicates providing GPs with a patient-focused strategy and associated materials doesn't increase the effects of peer comparison information.

Interestingly, the three peer comparison letters worked even better among the highest prescribers compared to moderately-high prescribers. We think this occurred because doctors further away from the average prescribing rate were more likely to see their behaviour as extreme. Despite this, our letters still reduced prescriptions among prescribers in the 70th to 85th percentile, suggesting there may be benefit in lowering the threshold to include prescribers below the 70th percentile. Future research could be undertaken to determine whether the potentially diminishing effects for lower prescribers are worth the impost of the intervention being applied to a broader range of people.

Comparison to similar trials

A similar trial of peer comparison letters in the UK (Hallsworth, 2016) reported a smaller reduction in prescription rates (3.3 per cent). We think this is due to the difference in the type of feedback. The UK study provided feedback to GPs about how their clinic was prescribing compared to other clinics in their local area. In contrast, our trial provided feedback to doctors about their individual prescribing rates compared to their peers. The differences in the two trials suggests peer comparison feedback has a larger impact when provided to individuals.

A recent US trial provided monthly, individual peer comparison feedback via email to clinicians on prescriptions for antibiotic-inappropriate diagnoses. Feedback was sent to all clinicians regardless of whether they were high or low prescribers. The authors found a smaller reduction in antibiotic scripts than our trial (when comparing treatment and control groups), but one which was still present after 18 months (Meeker et al., 2016). This suggests repeated peer comparison feedback could be an effective, low-cost strategy to reduce overprescribing over longer periods of time than assessed in our trial.

Future directions

An open question is how long the effects of this type of peer comparison intervention last. This is important for policy makers in designing these types of interventions, including whether follow-up letters may be required to maintain the effects and how frequently they should occur.

At the end of the six-month period, our peer comparison letters were causing smaller but still substantial reduction in prescribing rates. This implies that the letters' effect continues beyond six months and we look forward to analysing the data at the 12-month mark to ascertain how long the effect lasts.

We are also interested in whether follow-up letters would have the same impact, how often they should be sent, and whether repeat exposure reduces the effect. Follow-up letters could test the effect of including feedback on whether the doctor has increased or decreased their prescribing rates over time.

There are other prescribing issues of public importance where trialling a peer comparison feedback intervention may be appropriate. For example, several overseas jurisdictions are facing crises in the widespread misuse of prescribed opioids and there are concerns Australia is trending down a similar path.

Conclusion

The results of our trial show a peer comparison letter from a high profile and respected individual – Australia's CMO – can successfully impact the antibiotic prescribing habits of Australian GPs. These results are consistent with similar trials conducted in the UK and the US, providing evidence peer comparison interventions focused on antibiotic prescribing can work across countries.

Our findings can help inform future efforts to reduce the risk of AMR caused by the overprescribing of antibiotics. They suggest that antibiotic stewardship programs can maximise their effects by using peer comparison feedback at the individual-level to assist doctors to reflect on their prescribing practices.

Our results add to the large body of evidence that peer comparison can be a powerful behavioural tool for policy makers, particularly when using individual-level feedback. They also demonstrate that some of the impact of peer comparison interventions is sustained over a reasonable period of time. This should inspire policy makers to seek other opportunities for similar peer comparison interventions and to test the impact of repeating the intervention at intervals to see if the impact can be sustained over even longer periods.

Appendices

Appendix A: Technical details

Overview

We conducted a cluster randomised field experiment. The units of randomisation (clusters) were clinics containing GPs who were 'high prescribers' relative to other GPs in their region. The GPs in clusters assigned to treatments received individually addressed letters and we examined their individual prescription rates subsequently.

Treatment letters were sent to GPs on 9 June 2017, and the number of antibiotic scripts filled was monitored from this date to 9 December 2017.

Pre-registration, pre-analysis plan and ethics

We pre-registered this trial on both the American Economic Association RCT Registry and the BETA website shortly after the trial commenced but prior to accessing or analysing any data on outcomes. This pre-registration includes a detailed pre-analysis plan containing details for our proposed analysis. We made only very minor deviations from this pre-analysis plan (described 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.

Outcome

We focused on prescriptions of eight commonly prescribed antibiotics (see **Table 3**). Our dataset recorded the number of antibiotic scripts prescribed by GPs that were taken to a pharmacy and filled.

As the number of consults delivered by GPs varies and affects the number of prescriptions, we examined the number of antibiotic scripts filled per 1,000 consults for each GP.

Table 3: Antibiotics used in trial to calculate prescribing percentile

Antibiotic Name
Amoxicillin
Cephalexin
Amoxicillin with Clavulanic Acid
Roxithromycin
Clarithromycin
Erythromycin
Cefaclor
Trimethoprim with Sulfamethoxazole

Population and sampling

Our population of interest was GPs classified as 'high prescribers' relative to their peers. We defined a 'high prescriber' as a GP in the top 30 per cent of antibiotic prescribers in their region based on their prescription rate over the 12 months before the trial. We defined regions using the ABS Statistical Area Level 4 (SA4) – sub-state areas of approximately 100,000-300,000 residents.

We wanted to minimise the potential for including GPs who were on leave or who had recently retired or left the discipline. Consequently, prior to randomisation, we removed GPs with no consults or prescriptions in the previous three months. We also removed GPs with less than 50 scripts or less than 500 consults over the course of the previous 12 months, as this is a low level of activity for a GP. There was also a small number of prescribers with prior prescribing rates that were well above the average prescription rate. To deal with this, we removed the top 2 per cent of prescribers.

After these pre-randomisation exclusions had been made, we were left with 22,310 individual GPs. We divided these GPs into regions and selected the top 30 per cent of prescribers in each region. This gave a final sample of 6,649 individual GPs across 87 regions, which represented the entire study population of interest.

Clustering and spillover effects

It is possible that GPs within the same clinic (or beyond) would talk to one another about correspondence they received from the CMO. If we assigned different GPs in the same clinic to both treatment and control conditions, or to different types of treatments (letters), this could create 'spillover effects' if the GPs shared information contained in the letters with their colleagues. To reduce this possibility, we clustered our trial at the clinic/practice level. Our 6,649 individual GPs were grouped into 3,198 clusters, with an average of two GPs to a cluster. This still left a small possibility of spillover effects arising from conversations between GPs in different clinics but we judge this would have had a very low impact on our results (and only in the direction of attenuating treatment effects).

Power calculations and sample size

Prior to randomisation, we used our sample to perform power calculations.

We used historical prescription data to calculate a design effect to take into account the clustered randomisation. We calculated an intracluster correlation coefficient of 0.26, an average cluster size of 2.07, and from these a design effect of 1.28.

Looking at the historical data, we also found that past prescriptions explained 25 per cent of the variation in the present prescription rate. Thus, after adjusting for past prescriptions and applying our design effect, we calculated that a sample size of approximately 1,330 per group would provide 90 per cent power at a 5 per cent significance level to detect a 2.75 per cent reduction in the antibiotic prescription rate (from 104 to 97.7 scripts per 1,000 consults).

Matching and randomisation

Cluster randomised trials can return biased estimates if cluster size is related to the outcome (Middleton & Aronow, 2011). In order to protect against this, prior to randomising, we created groups of five clinics that were matched as closely as possible on the number of high prescribers in the clinics. We also matched on the average past prescription rate in the clinic and the socioeconomic status of area the clinic was located in (using the ABS Socio-Economic Indexes for Areas (SEIFA) score).

Within each matched group, we randomised clinics to our five trial arms. The result was approximately 640 clinics in each of the five arms, with each arm containing approximately 1,330 individual GPs.

Method of analysis

The principal analysis of the effect of the intervention was an adjusted comparison of our primary outcome 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:

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

Where α is the intercept, T_i is a vector of indicators for treatment group membership, x_i is a vector of mean-centred covariates, $x_i T_i$ is an interaction between treatment group indicators and the mean-centred covariates, v represents the error for each cluster *j,* and ω is an individual error term which picks up any variance not explainable by group membership, treatment indicators or covariates. As per our pre-analysis plan, we included the following covariates: the average prescription rate over the 12 months preceding the trial, prescriber age, and prescriber sex. These variables were interacted with the treatment indicator as per Lin (2013).

Because of missing data (discussed further below), it would have been difficult to account for matching since it requires dropping entire blocks of five units when data is missing in one group. Thus, we did not include indicators for each match in our estimating equations. We anticipated this decision in our pre-analysis plan.

As recommended by Imbens and Kolesár (2016), we performed the Bell McCaffrey adjustment for standard errors and CI. This involved calculating a bias-reduced cluster robust standard error (CR2) along with a degrees of freedom adjustment.

We also ran robustness checks using a version of this model with a log-transformed outcome variable, and another using a negative binomial regression with scripts as the outcome and consults as an offset. Both models produced similar results. These results are available on request.

Time series

To estimate changes in the intervention's effectiveness over time, we present individual regressions for each month. We also modelled the monthly effects of the intervention via a mixed effects model. This model included fixed effects for treatment, time, time interacted with treatment and baseline covariates, and random effects for GPs and GPs in clinics. The estimates from this model were qualitatively equivalent to the estimates from the individual monthly regressions. The results from the mixed effects model are available on request.

Data, exclusions and missingness

Data were extracted from the Medicare Benefits Schedule and Pharmaceutical Benefits Scheme database.

GPs with no recorded consults for a period were treated as missing and were excluded from analyses for the period (but were included for other periods if they had consult data). As a robustness check, we imputed rates for these individuals based on their pre-trial prescription rate. This did not alter our estimates.

We found a very small number of large outliers in our data (some as large as 375 standard deviation units). Including these in the analysis substantially altered our results. We did not address this possibility in our pre-analysis plan. In order to apply a consistent rule for removing implausible cases, we excluded any GP who had more scripts than consults. We picked this rule because it is not usual to prescribe more than one script for every consult. This effectively removed any observation with a rate above 1,000 scripts per 1,000 consults (about 24 standard deviation units). For the six-month pooled analysis we removed two units based on this rule – both had prescription rates above 15,000 scripts per 1,000 consults and were missing data for five out of six months. For the individual month analysis, we removed a total of 25 units. **Table 10** shows missingness and exclusions by treatment group.

Impact on the number of scripts

We also looked at the impact of our letters on the raw number of scripts filled.
We used a regression model with the same specification outlined in the 'Method of analysis section', however, we used number of scripts for the outcome variable.
We used this model to predict the number of scripts that would have been filled had all units been in the control group and the number filled if all units had been in the *peer comparison with graph* group.

Subgroup analyses

We pre-registered one subgroup comparison – comparing treatment effects between prescribers between the 70th and 85th percentile and those above the 85th percentile. As specified in our pre-analysis plan, we pooled our three peer comparison letter groups for this analysis. We also performed a number of secondary subgroup analyses. Because we did not power the study for these, and because of potential issues with multiple comparisons, these results should be interpreted with caution.

We 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.

Appendix B: 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:

- the results of the primary analysis – over six months and monthly – in **Table 4** and **Table 5**
- the pre-randomisation characteristics and descriptive statistics for the study population in **Table 6** and **Table 7**
- subgroup analyses (for high or moderate prescribing rates, age, sex, and socioeconomic status) in **Table 8** and **Table 9**
- missing data and exclusions in **Table 10**.

Table 4: Primary analysis – rates pooled over six months

	n	Adjusted mean	Treatment – Control effect (95 per cent CI)	p-value	Treatment-Education-only effect (95 per cent CI)	p-value
Control	1,332	109.3				
Education-only	1,305	105.8	-3.5 (-6.2 to -0.8)	0.013		
Education with peer comparison	1,302	99.2	-10.2 (-13.7 to -6.6)	< 0.00001	-6.7 (-10 to -3.4)	0.00007
Peer comparison with delayed prescribing	1,339	97.9	-11.5 (-14.5 to -8.5)	< 0.00001	-8 (-10.7 to -5.3)	< 0.00001
Peer comparison with graph	1,322	95.8	-13.6 (-16.6 to -10.6)	< 0.00001	-10.1 (-12.8 to -7.4)	< 0.00001

Note: Means and treatment effects are in scripts filled per 1,000 consults. *n* is the group sample size taking into account exclusions and missing data. Adjusted means, treatment estimates, 95 per cent CI and p-value are from a linear regression model adjusted for GPs' previous prescription rate, age and sex. We used robust standard errors (CR2) with a degrees of freedom adjustment.

Table 5: Primary analysis – monthly treatment effects

	Education-only		Education with peer comparison		Peer comparison with delayed prescribing		Peer comparison with graph	
	Estimate (CI)	p	Estimate (CI)	p	Estimate (CI)	p	Estimate (CI)	p
June (pre-trial)	-1.8 (-5.4 to 1.9)	0.34	-2.1 (-5.3 to 1.1)	0.20	-0.8 (-4.3 to 2.7)	0.65	-3.2 (-6.4 to 0)	0.05
Jul (month 1)	-1.3 (-5 to 2.3)	0.47	-12.2 (-15.6 to -8.8)	#	-11.2 (-14.7 to -7.7)	#	-12.2 (-16.2 to -8.1)	#
Aug (month 2)	-4 (-7.4 to -0.5)	0.02	-14.8 (-18.5 to -11.2)	#	-15.5 (-19.3 to -11.7)	#	-17.3 (-20.9 to -13.7)	#
Sep (month 3)	-4 (-8 to -0.1)	0.04	-14.9 (-18.7 to -11.1)	#	-15.2 (-19.2 to -11.2)	#	-16.6 (-20.7 to -12.6)	#
Oct (month 4)	-2.7 (-6.8 to 1.5)	0.21	-10.2 (-14.4 to -6.1)	#	-12.3 (-16.3 to -8.3)	#	-13 (-17.2 to -8.8)	#
Nov (month 5)	-3.1 (-5.9 to -0.2)	0.04	-7.7 (-10.8 to -4.6)	#	-6.9 (-9.9 to -3.8)	#	-7.9 (-11.1 to -4.7)	#
Dec (month 6)	-1.6 (-4.8 to 1.5)	0.30	-6.5 (-9.6 to -3.4)	#	-6.6 (-9.8 to -3.5)	#	-7.8 (-11 to -4.7)	#

Note: # = p-value less than 0.00001. Treatment effects are in scripts filled per 1,000 consults. These estimates, 95 per cent CI and p-values are from a linear regression model adjusted for GPs' previous prescription rate, age and sex with robust standard errors (CR2) and a degrees of freedom adjustment. Regressions were estimated individually for each month.

Table 6: Pre-randomisation characteristics

		Control	Education-only	Education with peer comparison	Peer comparison with delayed prescribing	Peer comparison with graph
GPs (n)		1,338	1,319	1,311	1,348	1,333
Clinics (n)		640	639	639	640	640
Pre-trial prescriptions (mean ± SD)		100.5 ± 23.9	99.7 ± 24.8	99.5 ± 23.8	99.9 ± 23.9	100.8 ± 25.2
Average rank (mean ± SD)		84.7 ± 8.5	84.7 ± 8.7	84.8 ± 8.8	85 ± 8.5	85.3 ± 8.6
Age (mean ± SD)		51.5 ± 11.8	51.5 ± 11.5	51.6 ± 11.8	51.5 ± 11.9	51 ± 11.6
SEIFA (mean ± SD)		993.6 ± 74.5	995.6 ± 72.1	993.5 ± 74	996.8 ± 73.9	993.4 ± 74
Male (%)		65.5	63.2	62.6	67.0	64.8
State/territory (%)	ACT / NSW	29.2	34.3	32.9	37.5	32.6
	NT	0.4	0.7	0.7	0.7	0.6
	QLD	27.2	18.6	21.1	16.3	19.9
	SA	7.4	6.7	6.6	8.9	8.6
	VIC / TAS	26.8	30.8	29.7	27.8	27.5
	WA	9.0	9.0	9.0	8.8	10.8

Note: Table reports all units in trial without exclusions. SEIFA is the ABS SEIFA score. Pre-trial prescriptions are the average prescription rate for GPs over the full year before the trial.

Table 7: Descriptive statistics – scripts, consults and rates (mean ± SD)

		Jul – Dec combined	Jun (pre-trial)	Jul	Aug	Sep	Oct	Nov	Dec
Control	Scripts	298.1 ± 222.0	50.8 ± 39.2	49.4 ± 38.9	59.9 ± 47.1	62.2 ± 49.1	50.3 ± 39.8	44.3 ± 34.0	39.3 ± 30.4
	Consults	2690.3 ± 1603.4	483.8 ± 291.8	419.1 ± 259.8	494.4 ± 299.7	497.8 ± 302.8	442.2 ± 273.6	468.8 ± 282.9	434.0 ± 265.7
	Rate	109.7 ± 40.8	103.9 ± 52.4	114.5 ± 44.7	118.8 ± 48.6	122.6 ± 53.4	113.2 ± 54.3	93.3 ± 36.8	89.1 ± 38.4
Education-only	Scripts	288.2 ± 216.5	49.7 ± 39.3	48.5 ± 39.5	57.9 ± 46.2	59.0 ± 46.9	48.2 ± 39.0	42.0 ± 33.1	38.0 ± 29.3
	Consults	2667.2 ± 1565.8	483.5 ± 285.5	418.6 ± 262.2	489.3 ± 294.8	485.1 ± 291.9	435.5 ± 269.2	459.2 ± 275.9	431.3 ± 258.2
	Rate	105.5 ± 37.7	101.4 ± 55.5	112.6 ± 52.5	113.9 ± 45.5	117.8 ± 50.2	109.7 ± 52.7	89.7 ± 37.2	86.8 ± 40.8
Education with peer comparison	Scripts	259.3 ± 199.2	49.6 ± 40.0	42.6 ± 35.4	50.8 ± 41.4	52.9 ± 43.1	44.1 ± 35.3	39.5 ± 31.3	35.4 ± 28.1
	Consults	2627.4 ± 1606.0	476.9 ± 291.0	409.2 ± 264.8	480.3 ± 298.0	484.5 ± 303.3	429.5 ± 269.0	458.8 ± 282.1	426.6 ± 264.1
	Rate	98.7 ± 50.1	100.7 ± 38.7	101.5 ± 41.9	103.0 ± 45.0	106.7 ± 47.1	102.1 ± 50.1	84.9 ± 36.7	81.7 ± 37.0
Peer comparison with delayed prescribing	Scripts	272.6 ± 202.1	52.4 ± 39.5	45.4 ± 36.8	53.5 ± 43.3	55.5 ± 44.4	46.1 ± 36.2	41.5 ± 30.5	36.9 ± 27.5
	Consults	2768.3 ± 1660.1	498.9 ± 293.8	434.3 ± 279.1	510.0 ± 311.6	508.7 ± 312.6	455.0 ± 280.1	482.3 ± 289.0	444.2 ± 266.2
	Rate	97.9 ± 38.9	102.4 ± 46.8	103.0 ± 50.0	102.7 ± 49.2	106.9 ± 49.0	100.4 ± 42.9	86.0 ± 37.3	82.1 ± 37.0
Peer comparison with graph	Scripts	267.5 ± 198.4	52.1 ± 40.4	43.6 ± 34.4	51.6 ± 40.2	53.5 ± 43.6	45.8 ± 37.0	41.3 ± 33.0	36.2 ± 28.3
	Consults	2754.6 ± 1564.3	498.1 ± 288.2	427.9 ± 260.9	502.6 ± 295.8	495.6 ± 295.9	452.8 ± 268.6	480.3 ± 281.0	441.9 ± 259.4
	Rate	96.2 ± 37.4	100.9 ± 40.4	102.5 ± 59.2	101.4 ± 44.6	105.9 ± 51.3	100.3 ± 46.3	85.6 ± 41.5	81.3 ± 37.0

Note: This table shows raw (unadjusted) group means ± SDs for scripts, consults and prescription rates (scripts per 1,000 consults). Averages were calculated after exclusions were made to the sample.

Table 8: Pooled effect of the three peer comparison letters by prescribing level

Subgroup	Prescriber level	Treatment – Control difference (95 per cent CI)	p-value	Difference across levels (95 per cent CI)	p-value
July (month 1)	Moderately-high	-9.2 (-12.8 to -5.6)	< 0.0001		
	Highest	-14.5 (-18.7 to -10.4)	< 0.0001	-5.3 (-10.5 to -0.2)	0.04
August (month 2)	Moderately-high	-10.5 (-13.7 to -7.3)	< 0.0001		
	Highest	-21.9 (-26.5 to -17.3)	< 0.0001	-11.3 (-16.4 to -6.2)	< 0.0001
September (month 3)	Moderately-high	-12.5 (-16.9 to -8.1)	< 0.0001		
	Highest	-18.8 (-23.2 to -14.5)	< 0.0001	-6.2 (-12.1 to -0.4)	0.04
October (month 4)	Moderately-high	-10.3 (-14.3 to -6.3)	< 0.0001		
	Highest	-13.7 (-18.8 to -8.6)	< 0.0001	-3.3 (-9.3 to 2.7)	0.28
November (month 5)	Moderately-high	-5.2 (-8.0 to -2.4)	0.0003		
	Highest	-10.1 (-13.7 to -6.4)	< 0.0001	-4.8 (-8.9 to -0.7)	0.02
December (month 6)	Moderately-high	-4.9 (-7.6 to -2.2)	0.0003		
	Highest	-9.2 (-13.6 to -4.8)	< 0.0001	-4.2 (-9.0 to 0.7)	0.09

Note: Moderately-high prescribers refer to GPs between the 70th and 85th prescribing percentile. Highest prescribers are above the 85th percentile. This analysis was performed using a linear regression model adjusted for previous prescription, age and sex using cluster robust standard errors. The difference across levels was tested by interacting an indicator for 'highest prescribing' with an indicator for treatment. In this table the treatment group is the three peer comparison letter groups combined.

Table 9: Pooled effect of the three peer comparison letters by subgroup

Subgroup	Level	Treatment – Control difference (95 per cent CI)	p-value	Difference across levels (95 per cent CI)	p-value
Socioeconomic status of the area	Low	-15.3 (-18.9 to -11.7)	< 0.0001		
	High	-8.3 (-11.8 to -4.7)	< 0.0001	7 (1.9 to 12)	0.007
Age	<51	-13.2 (-17.3 to -9)	< 0.0001		
	51+	-10.7 (-13.5 to -7.9)	< 0.0001	2.5 (-2.3 to 7.3)	0.3
Sex	Female	-12.6 (-17.2 to -8.1)	< 0.0001		
	Male	-11.3 (-14.1 to -8.6)	< 0.0001	1.3 (-3.8 to 6.3)	0.6

Note: Subgroup analyses were performed using a linear regression model adjusted for previous prescription, age and sex (when age or sex were not the subject of the subgroup analysis) with cluster robust standard errors. The difference across levels was tested by interacting an indicator for subgroup membership with an indicator for treatment. In this table the treatment group is the three peer comparison letter groups combined.

Table 10: Missing data and exclusions

		Control	Education-only	Education with peer comparison	Peer comparison with delayed prescribing	Peer comparison with graph
Jul – Dec combined	**Missing**	**6 (0.5%)**	**14 (1.1%)**	**9 (0.7%)**	**8 (0.6%)**	**10 (0.8%)**
	Excluded	**0 (0%)**	**0 (0%)**	**0 (0%)**	**1 (0.001%)**	**1 (0.001%)**
Jul (month 1)	Missing	29 (2.2%)	28 (2.1%)	28 (2.1%)	29 (2.2%)	26 (2.0%)
	Excluded	1 (0.007%)	1 (0.008%)	0 (0%)	2 (0.002%)	2 (0.002%)
Aug (month 2)	Missing	30 (2.2%)	32 (2.4%)	32 (2.4%)	35 (2.6%)	28 (2.1%)
	Excluded	3 (0.002%)	4 (0.003%)	0 (0%)	2 (0.002%)	1 (0.001%)
Sep (month 3)	Missing	41 (3.1%)	35 (2.7%)	44 (3.4%)	34 (2.5%)	31 (2.3%)
	Excluded	0 (0%)	0 (0%)	1 (0.001%)	1 (0.001%)	1 (0.001%)
Oct (month 4)	Missing	41 (3.1%)	45 (3.4%)	39 (3.0%)	41 (3.0%)	36 (2.7%)
	Excluded	0 (0%)	1 (0.008%)	0 (0%)	2 (0.002%)	1 (0.001%)
Nov (month 5)	Missing	41 (3.1%)	45 (3.4%)	42 (3.2%)	45 (3.3%)	34 (2.6%)
	Excluded	0 (0%)	0 (0%)	0 (0%)	1 (0.001%)	0 (0%)
Dec (month 6)	Missing	40 (3.0%)	47 (3.6%)	44 (3.4%)	48 (3.6%)	38 (2.9%)
	Excluded	1 (0.007%)	0 (0%)	2 (0.002%)	0 (0%)	0 (0%)

Note: This table shows the number of GPs for whom we had missing data, and the number we excluded because prescriptions were greater than consults for each month.

Appendix C: Letters

1. Education-only letter and materials

Australian Government
Department of Health

CHIEF MEDICAL OFFICER

<00 Month 0000> Your reference: <reference #>

<Title> <Name> <Surname>
<Address Line 1>
<Address Line 2>
<SUBURB> <STATE> <Postcode>

Dear Dr <Surname>

Australia is committed to preserving the effectiveness of antibiotics. General Practitioners are important partners in our efforts to minimise antimicrobial resistance by helping limit community prescribing to only those clinical situations where evidence shows antibiotics to be of proven value.

Antimicrobial resistance is an urgent global health priority. The World Health Organization (WHO) describes it as a looming crisis in which common and treatable infections are becoming life threatening. You may be aware of the patient in the USA who died earlier this year with a Klebsiella infection that was untreatable, due to resistance to all available antibiotics. We have also seen cases of highly resistant gram negative bacteria in Australia.

Globally, resistance is increasing at a pace that far exceeds our capacity to develop new antimicrobial drugs, very few of which have been brought to market in recent years.

As antimicrobial resistance continues to grow, Australia is likely to experience clinical situations already seen in other countries where:

- Routine surgical procedures, such as caesarean sections, become a much higher risk.
- Transplant programs have to be halted and Intensive Care Units closed to deal with contamination with highly resistant organisms.
- Pneumonia, gonorrhoea and even urinary tract infections are becoming increasingly more difficult to treat.
- Rising medical costs and mortality rates are attributable to infection increase.

I know that antimicrobial resistance is a complex issue that requires concerted efforts across general practice, hospitals, laboratories and animal health professionals. However, there is clear evidence that reducing unnecessary prescribing can lower the incidence of antimicrobial resistance. The benefits of tackling this problem are relevant to every one of our patients.

GPO Box 9848 Canberra ACT 2601

You can help by:

- prescribing antibiotics only in situations where evidence shows that they are clearly needed.
- educating your patients on the correct use of antibiotics and why they might not always be appropriate for conditions such as viral upper respiratory tract infections.
- promoting infection control within your practice.

I have also attached two posters from the National Prescribing Service. One is intended for patients and the other for General Practitioners. These outline what patients and doctors can do to reduce the overprescribing of antibiotics, which you may find useful in your practice.

For more information about what you can do to address antimicrobial resistance in your practice, go to **www.nps.org.au/amr**.

To discuss the contents of this letter please contact the Department of Health on 1800 316 386.

Yours sincerely

Professor Brendan Murphy
Chief Medical Officer


Are you an antibiotic misuser?
Misusing antibiotics can cause harm.
Handle them with care.
For more information visit nps.org.au/misuser
NPS MEDICINEWISE
This initiative is funded by the Australian Government Department of Health.


ANTIBIOTIC RESISTANCE
One of the GREATEST THREATS to human health
Without action now, by 2050 up to
10 MILLION
people may die EVERY YEAR
from untreatable infections
10M
NOW
2050
OVERUSE AND MISUSE of antibiotics is leading to an increasing number of antibiotic-resistant infections appearing in Australia
Multidrug-resistant gonorrhoea
Multidrug-resistant tuberculosis
Reported resistance to fluoroquinolones, carbapenem, and first line therapies for common infections
Without EFFECTIVE antibiotics many conditions will become UNTREATABLE
BE PART OF THE SOLUTION
Rx
Only prescribe and dispense antibiotics when truly needed
Educate your patients to take the right dose for the right duration and never share or use leftovers
Practise good infection control
For more information visit
nps.org.au/amr
NPS MEDICINEWISE
PROFESSIONAL

2. Education with peer comparison letter and attached posters

Australian Government
Department of Health

CHIEF MEDICAL OFFICER

<00 Month 0000> Your reference: <reference #>

Dr <First Name> <Last Name>
<Address Line 1>
<Address Line 2>
<SUBURB> <STATE> <Postcode>

Dear Dr <Last Name>

You prescribe more antibiotics than <x%> of prescribers in <region 1>

Australia is committed to preserving the effectiveness of antibiotics. General Practitioners are important partners in our efforts to minimise antimicrobial resistance by helping limit community prescribing to only those clinical situations where evidence shows antibiotics to be of proven value.

Antimicrobial resistance is an urgent global health priority. The World Health Organization (WHO) describes it as a looming crisis in which common and treatable infections are becoming life threatening. You may be aware of the patient in the USA who died earlier this year with a Klebsiella infection that was untreatable, due to resistance to all available antibiotics. We have seen cases of highly resistant gram negative bacteria also in Australia.

Globally, resistance is increasing at a pace that far exceeds our capacity to develop new antimicrobial drugs, very few of which have been brought to market in recent years.

As antimicrobial resistance continues to grow, Australia is likely to experience clinical situations already seen in other countries where:

- Routine surgical procedures, such as caesarean sections, become a much higher risk.
- Transplant programs have to be halted and Intensive Care Units closed to deal with contamination with highly resistant organisms.
- Pneumonia, gonorrhoea and even urinary tract infections are becoming increasingly more difficult to treat.
- Rising medical costs and mortality rates are attributable to infection increase.

I know that antimicrobial resistance is a complex issue that requires concerted efforts across general practice, hospitals, laboratories and animal health professionals. However, there is clear evidence that reducing unnecessary prescribing can lower the incidence of antimicrobial resistance. The benefits of tackling this problem are relevant to every one of our patients.

GPO Box 9848 Canberra ACT 2601

You can help by:

- prescribing antibiotics only in situations where evidence shows that they are clearly needed.
- educating your patients on the correct use of antibiotics and why they might not always be appropriate for conditions such as viral upper respiratory tract infections
- promoting infection control within your practice.

I have also attached two posters from the National Prescribing Service. One is intended for patients and the other for General Practitioners. These outline what patients and doctors can do to reduce the overprescribing of antibiotics, which you may find useful in your practice.

For more information about what you can do to address antimicrobial resistance in your practice, go to **www.nps.org.au/amr**.

To discuss the contents of this letter please contact the Department of Health on 1800 316 386.

Yours sincerely

Professor Brendan Murphy
Chief Medical Officer

Your estimated antibiotics prescribing between 1 April 2016 and 31 March 2017

The Pharmaceutical Benefits Scheme (PBS) data has been provided to you as a prompt to consider your prescribing behaviour. The table below shows a break-down of your PBS prescriptions that have been dispensed. This includes raw numbers of prescriptions dispensed for concession card holders, PBS items above the co-payment and PBS items below the co-payment.

Antibiotic	Number of prescriptions dispensed
Amoxicillin	X
Cephalexin	X
Amoxicillin with Clavulanic Acid*	X
Roxithromycin	X
Clarithromycin	X
Erythromycin	X
Cefaclor	X
Trimethoprim with Sulfamethoxazole	X
Total	**X**

Number of consultations	X
Prescription rate (per 1000 consultations)	X
Your prescribing percentile	X

*This medication is restricted under the PBS to infections where resistance to amoxicillin is suspected or proven.

How we calculated your prescribing percentile

Your estimated prescribing rate is your dispensed antibiotic prescriptions as a proportion of Medicare Benefits Scheme (MBS) consults (at a rate of 1,000 consults). To determine your percentile, your rate was compared with the average rate for GPs in your area. Your area (<region 2>) is based on Australian Bureau of Statistics Statistical Area Level 4, which is made up of approximately <region pop> people.

The educational posters attached to this letter are shown below. These posters were the same as those attached to the education-only letter. See pg. 44-45 for full-size images of these posters.

3. Peer comparison with graph letter

Australian Government

Department of Health

CHIEF MEDICAL OFFICER

<00 Month 0000> Your reference: <reference #>

Dr <First Name> <Last Name>
<Address Line 1>
<Address Line 2>
<SUBURB> <STATE> <Postcode>

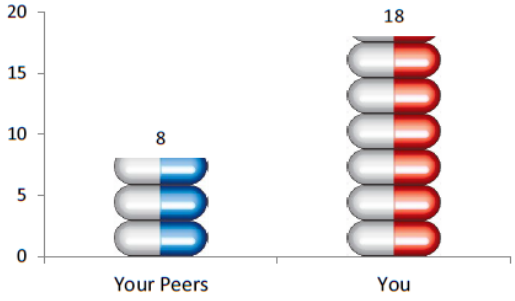
Dear Dr <Last Name>

You prescribe more antibiotics than <x%> of prescribers in <region 1>

Australia is committed to preserving the effectiveness of antibiotics. General Practitioners are important partners in our efforts to minimise antimicrobial resistance by helping limit community prescribing to only those clinical situations where evidence shows antibiotics to be of proven value.

You prescribed the following antibiotics between 1 April 2016 and 31 March 2017.

Number of scripts dispensed per 1000 consults



Your detailed antibiotic prescribing numbers are provided on the next page.

I know that antimicrobial resistance is a complex issue that requires concerted efforts across general practice, hospitals, laboratories and animal health professionals. However, there is clear evidence that reducing unnecessary prescribing can lower the incidence of antimicrobial resistance. The benefits of tackling this problem are relevant to every one of our patients.

GPO Box 9848 Canberra ACT 2601

For more information about what you can do to address antimicrobial resistance in your practice, go to **www.nps.org.au/amr**.

To discuss the contents of this letter please contact the Department of Health on 1800 316 386.

Yours sincerely

Professor Brendan Murphy
Chief Medical Officer

Your estimated antibiotics prescribing between 1 April 2016 and 31 March 2017

The Pharmaceutical Benefits Scheme (PBS) data has been provided to you as a prompt to consider your prescribing behaviour. The table below shows a break-down of your PBS prescriptions that have been dispensed. This includes raw numbers of prescriptions dispensed for concession card holders, PBS items above the co-payment, and PBS items below the co-payment.

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Amoxicillin	X
Cephalexin	X
Amoxicillin with Clavulanic Acid*	X
Roxithromycin	X
Clarithromycin	X
Erythromycin	X
Cefaclor	X
Trimethoprim with Sulfamethoxazole	X
Total	**X**

Number of consultations	X
Prescription rate (per 1000 consultations)	X
Your prescribing percentile	X

*This medication is restricted under the PBS to infections where resistance to amoxicillin is suspected or proven.

How we calculated your prescribing percentile

Your estimated prescribing rate is your dispensed antibiotic prescriptions as a proportion of Medicare Benefits Scheme (MBS) consults (at a rate of 1,000 consults). To determine your percentile, your rate was compared with the average rate for GPs in your area. Your area (<region 2>) is based on Australian Bureau of Statistics Statistical Area Level 4, which is made up of approximately <region pop> people.

4. Peer comparison with delayed prescribing and NPS action plan (example of a sticker is on right hand corner of letter)

used alongside a *Delayed Prescribing Sticker* to provide instructions to the patient on how to manage their symptoms.

Under the 'additional advice and actions' section of the *Action Plan,* you can provide clear instructions on when to fill the script if symptoms don't improve in accordance with the expected course of the illness or advice on re-consulting if there is a worsening of symptoms.

I have attached references about delayed prescribing that may be of interest to you.

More information
Your detailed antibiotic prescribing numbers are below.

I know that antimicrobial resistance is a complex issue that requires concerted efforts across general practice, hospitals, laboratories and animal health professionals. However, there is clear evidence that reducing unnecessary prescribing can lower the incidence of antimicrobial resistance. The benefits of tackling this problem is relevant to every one of our patients.

For more information about what you can do to address antimicrobial resistance in your practice, go to **www.nps.org.au/amr**.

To discuss the contents of this letter please contact the Department of Health on 1800 316 386.

Yours sincerely

Professor Brendan Murphy
Chief Medical Officer

Your estimated antibiotics prescribing between 1 April 2016 and 31 March 2017

The Pharmaceutical Benefits Scheme (PBS) data has been provided to you as a prompt to consider your prescribing behaviour. The table below shows a break-down of your PBS prescriptions that have been dispensed. This includes raw numbers of prescriptions dispensed for concession card holders, PBS items above the co-payment, and PBS items below the co-payment.

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Amoxicillin with Clavulanic Acid*	X
Roxithromycin	X
Clarithromycin	X
Erythromycin	X
Cefaclor	X
Trimethoprim with Sulfamethoxazole	X
Total	**X**

Number of consultations	X
Prescription rate (per 1000 consultations)	X
Your prescribing percentile	X

*This medication is restricted under the PBS to infections where resistance to amoxicillin is suspected or proven.

How we calculated your prescribing percentile
Your estimated prescribing rate is your dispensed antibiotic prescriptions as a proportion of Medicare Benefits Scheme (MBS) consults (at a rate of 1,000 consults). To determine your percentile, your rate was compared with the average rate for GPs in your area. Your area (<region 2>) is based on Australian Bureau of Statistics Statistical Area Level 4, which is made up of approximately <region pop> people.

Name:

ACTIONPLAN

RESPIRATORY TRACT INFECTIONS

Manage your symptoms

You have an infection of the ear, nose, throat, sinuses and/or chest, most likely caused by a virus. Antibiotics don't work against viral infections. Antibiotics won't make you feel better or recover faster.

What is a respiratory tract infection?

A respiratory tract infection is an infection anywhere in the respiratory tract (ie, the nose, throat and lungs). Your respiratory tract infection is most likely caused by a virus; antibiotics kill bacteria, not viruses.

How can I treat a viral respiratory tract infection?

Most coughs, earaches, sinus congestion problems and sore throats get better without antibiotics. Colds rarely cause serious harm, but they can still make you feel unwell. The good news is that colds usually get better in 7 to 10 days, although a cough can last up to 3 weeks and there are things you can do to feel better.

Contact your doctor

Contact your doctor if you don't begin to feel better after a few days, your symptoms worsen, new symptoms develop or you get side effects.

A respiratory tract infection can make an ongoing medical condition — such as asthma or diabetes — worse. Contact your doctor if this happens.

Additional advice and actions

What can you do?

Rest

- ☐ Allow your immune system to fight off the virus.

Use home remedies

- ☐ Gargle warm salty water.
- ☐ Suck on an ice cube or lozenge as needed.
- ☐ Have a soothing drink (eg, honey & lemon).
- ☐ Apply moisturiser to soothe dry skin of the nose.
- ☐ Inhale steam from the shower. Don't inhale steam from a bowl of hot water because of the risk of burns.

Use symptom-relieving medicines

- ☐ Use a decongestant nasal spray or drops.*
- ☐ Use saline nasal spray or drops.
- ☐ Take a decongestant tablet or mixture.*
- ☐ Take a non-prescription pain reliever medicine.

*Should not be given to children < 6 years of age & should only be given to children aged 6 to 11 years on the advice of a doctor, pharmacist or nurse practitioner.

Prevent the spread of infection

- ☐ Cover your mouth when sneezing or coughing.
- ☐ Clean your hands after blowing your nose.

To download a PDF version of this Action Plan or for instructions on how to retrieve it through your Clinical Information System, go to **www.nps.org.au/rti**

NPS MEDICINEWISE

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