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Does telemedicine technology affect prescribing quality in primary care? The case of antibiotics[☆]

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ABSTRACT

We study the impact of telemedicine technology on antibiotic prescription rates using linked administrative data from Australia on physicians and their patients. We classify physicians by their relative use of virtual consultations after the introduction of government-subsidised telemedicine services and compare their antibiotic prescribing rates before and after telemedicine services became available. We find that more intense telemedicine adopters prescribe less antibiotics while keeping prescribing quality unchanged. Our results are not explained by patient sorting, doctor shopping, or changes in the intensity of consultations.

1. Introduction

Technologies that improve efficiency of healthcare delivery are in high demand due to rapidly increasing healthcare costs. One such innovation that has recently gained significant attention is telemedicine which provides virtual healthcare services via video or telephone. The main appeal of telemedicine, or telehealth,[1] is that it can reduce physical and financial barriers for accessing

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[1] Although telehealth and telemedicine are often used interchangeably, they have different meanings. Telehealth includes *all* healthcare services that can be performed using remote communications technology (e.g., patient information services, self-care, and electronic prescribing of pharmaceuticals), telemedicine is defined more narrowly as the *practice of medicine* using remote means (e.g., diagnosing and treating patients). While the difference is not crucial in the context of our paper, we will use telemedicine throughout to avoid confusion.

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healthcare services preventing individuals from receiving the care they need (Berman and Fenaughty, 2005) as well as expanding their choice of care providers (Dahlstrand, 2022). Although most agree that telemedicine improves *access* to healthcare (Busso et al., 2022; Fu et al., 2024), some have argued that it does not reduce healthcare *spending* (Ashwood et al., 2017). Concerns also exist as to whether telemedicine compromises quality of care compared with face-to-face consultations (Willis et al., 2021).

In this paper, we exploit a natural experiment to study the effects of a nationwide rollout of telemedicine services in Australia on the prescribing behaviour of general practitioners (GPs). We base our analysis on the important case of antibiotics which, while crucial for treating many life-threatening bacterial infections, are also considered harmful due to associated negative externalities in the form of accelerated antimicrobial resistance (AMR) (Adda, 2020). Overconsumption of antibiotics is a key driver of AMR, which the OECD and WHO identify as one of the most pressing global health threats.[2] In 2019, it was estimated that five million deaths worldwide were associated with bacterial AMR, highlighting the urgent need for action (Murray et al., 2022). Without stronger antibiotic stewardship and prudent prescribing, health systems face escalating economic and social costs, including reduced productivity, more expensive second-line treatments, and greater risks during routine procedures (OECD, 2023).

Telemedicine may alter GPs prescribing patterns by reshaping how care is delivered and accessed. Several possible mechanisms exist wherein which telemedicine, compared with face-to-face consultations, can contribute to either increased or decreased antibiotic prescribing rates. First, remote consultations reduce time spent on travel and waiting, resulting in lower transaction costs for both patients and providers. GPs may be less inclined to prescribe antibiotics pre-emptively if they have an opportunity to schedule short follow-up consultations, leading to a reduction of 'just in case' prescriptions (Dahlstrand et al., 2025). Telemedicine also impact broader capacity–quality trade-offs in primary care by changing the opportunity cost of physician time. More efficient time use expands capacity and may reduce reliance on antibiotics as a substitute for limited consultation time among GPs (Shurtz et al., 2022). On the other hand, lower transaction costs for accessing drugs could also exacerbate overprescribing from excess demand, which has recently been documented following the rollout of electronic prescribing in Finland (Böckerman et al., 2025).

Furthermore, telemedicine also influences the diagnostic environment. Overprescribing may arise from a diminished physician ability to conduct in-depth patient examinations in virtual settings (Huang and Ullrich, 2024), resulting in an increase in precautionary antibiotic prescriptions (Miller, 2003; Scott et al., 2022). Conversely, increased physical remoteness could alleviate the real or perceived patient pressure that physicians feel in a face-to-face setting (Macfarlane et al., 1997; Hoffmann and Del Mar, 2015).[3] GPs might feel more confident in overruling patient preferences in favour of clinical guidelines on AMR in telemedicine consultations, thus reducing antibiotic prescribing rates (van De Pol et al., 2021; Wellsjo et al., 2025).

Finally, telemedicine increases patients' choice of healthcare provider by tearing down geographic access barriers. A larger choice set could improve matches between patients and more guideline-adherent physicians, thereby leading to lower rates of inappropriate antibiotic prescriptions (Dahlstrand, 2022). On the other hand, the recent rise of direct-to-consumer (DTC) telemedicine platforms have become popular online sources for rapid and convenient access to prescription medicine, but questions remain about the quality of the services they provide (Jain et al., 2019).

Our empirical framework leverages institutional features of Australia's governance structure in its responses to the COVID-19 pandemic. On the national level, the federal government legislated a rapid expansion of subsidised telemedicine services as a response to rising COVID-19 infection rates in early 2020.[4] Since the use of telemedicine in primary care was negligible before the pandemic, we employ a difference-in-differences design to compare changes in antibiotic prescribing rates of GPs who varied in the intensity with which they adopted telemedicine for their patient consultations following its nationwide rollout. Furthermore, the varying state government responses to and epidemiological contexts of the COVID-19 pandemic provide ample variation in local area telemedicine adoption to study mechanisms and factors underlying the diffusion of telemedicine services and implications for antibiotic prescribing policy.

To estimate our models, we use longitudinal individual-level data from the Australian Bureau of Statistics' Person Level Integrated Data Asset (PLIDA) database. PLIDA covers the universe of government-subsidised primary care services and prescribed pharmaceuticals from the Australian Medicare Benefits Schedule (MBS) and the Pharmaceutical Benefits Scheme (PBS). We construct a physician sample based on all GPs practising in Australia during the COVID-19 lockdown period in the second and third quarters of 2020 to estimate physician-specific intensities of telemedicine adoption.[5] We then use these physician-specific estimates to study associations between GPs' telemedicine adoption intensity and changes in antibiotic prescription rates and indicators of prescribing quality. To account for unobserved heterogeneity from pandemic-related healthcare disruptions, we compare changes in outcomes between the pre-telemedicine period, from 2017 until 2019, and the post-telemedicine period, from 2020 until 2022, for GPs practising in the same local area.

[2] Studies have shown that even short-term consumption of antibiotics may lead to a failure in subsequent treatments and to a potential spread of AMR (Jakobsson et al., 2010), which is considered one of the top 10 threats to public health declared by the World Health Organization (WHO). See https://www.who.int/news-room/fact-sheets/detail/antimicrobial-resistance.

[3] Patient pressure to prescribe antibiotics is a common problem in primary care. For example, Cole (2014) reported that more than half of surveyed physicians in England felt pressured to prescribe antibiotics even when not clinically indicated. In Australia, a recent poll issued by the Royal Australian College of General Practitioners, the peak body for general practice in Australia, suggested that 85 percent of surveyed GPs reported that they feel pressure from patients to prescribe antibiotics that are not clinically necessary, with one quarter of respondents indicating that this occurs on a daily basis. See https://www1.racgp.org.au/newsgp/professional/gps-feel-patient-pressure-for-unnecessary-prescrip.

[4] Similar policy changes were implemented in other countries, including Canada and the US (Mehrotra et al., 2021).

[5] Since virtually all GPs adopted telemedicine (i.e., used it for a patient consultation for the first time) almost immediately after such services were subsidised by Medicare, we focus on a continuous intensity measure to operationalise adoption in our analysis. Specifically, we use the share of telemedicine consultations as a fraction of all patient consultations.

We find that GPs who adopted telemedicine more intensively reduced their antibiotic prescription rates compared with low-intensity adopters. Specifically, our estimates show that antibiotic prescriptions rates per 100 patient consultations dropped by, on average, 0.6 scripts (5%) for GPs with above average telemedicine adoption intensity (high-intensity adopters) relative to GPs with below average adoption intensity (low-intensity adopters) after primary care telemedicine consultations became subsidised in Medicare. This effect is explained by both a relative increase in the number of consultations and a relative decrease in the total number of prescribed antibiotic scripts for high-intensity adopters, which also persist into the post-pandemic period.

To gauge whether changes in prescribing rates were associated with changes in adherence to antibiotic prescribing guidelines, we investigate the relative use of antibiotics predominantly prescribed for respiratory tract infections (RTIs). We focus on the shares of RTI-related antibiotics and broad-spectrum RTI-related antibiotics as proxy variables for non-guideline concordant (low-value) care. Our estimation results do not indicate important changes in the use of antibiotic prescriptions for RTIs between high- and low-intensity adopters of telemedicine.

We corroborate the robustness of our findings to several threats to causal identification, including demand-driven changes in the compositions of GPs' patient case-mix and endogenous changes in the frequency of consultations. To address the former issue, we control for GPs' patient mix by creating a risk-adjusted measure of each GP's patient population with respect to antibiotic use in the pre-pandemic period from 2013 to 2018. In terms of the latter, we replace our definition of a consultation with an episode measure, defined as all appointments that occur within a seven day period from an initial observed consultation for the same physician and patient pair. Our estimation results remain robust to both modifications.

Our empirical framework does not allow us to explicitly identify whether the effects we estimate for antibiotic prescribing arise from telemedicine itself, prescribing practices among GPs who adopted telemedicine more intensively, or a combination of both. The distinction is relevant insofar that our estimated effect is to be interpreted as an average treatment effect across all physicians, or as a local average treatment effect among physician 'compliers' to the telemedicine policy. Several arguments support an interpretation of our results as a direct effect of telemedicine, however. First, it is unlikely that our model is picking up a 'proficiency' effect among GPs who were both more likely to use telemedicine and better at diagnosing infections in virtual settings. The reason is that such proficiency should also be present in a face-to-face setting which is not supported by our event study pre-trends analysis. Furthermore, we do not find any difference in the responses of high- and low-intensity telemedicine adopters to prior influenza outbreaks in 2017 and 2019. However, regardless of the specific effect interpretation, it is important to remember that our results are causally identified as long as high- and low-intensity adopters would have prescribed antibiotics at the same relative rate in the absence of government-subsidised telemedicine services. This assumption is supported by our data.

Our paper contributes to the small but growing number of studies that analyse the relationship between quality of care and telemedicine (Uscher-Pines et al., 2015; Shi et al., 2018; Ray et al., 2019; Knies, 2024; Ganguli et al., 2025; Wellsjo et al., 2025) and, more broadly, health information technology (see, e.g., Atasoy et al., 2019; Böckerman et al., 2022, 2025). For example, Ray et al. (2019) examine claims data from a private insurance scheme in the United States, finding that paediatric patients with acute respiratory infections are more likely to receive antibiotic prescriptions in a telemedicine setting and that telemedicine consultations are less likely to elicit guideline-concordant antibiotic management. Our results contrast these findings in that we find reductions in the use of antibiotics and no indications of lower prescribing quality in telemedicine settings. One reason for the diverging findings could be that our analysis captures results from a more general population in a universal healthcare context. Moreover, Böckerman et al. (2025) find that the rollout of electronic prescribing in Finland improved continuity of care for elderly patients, but also highlight trade-offs from increased overuse of harmful opioids among younger individuals. We consider the possibility that telemedicine improves access to care but may also reduce diagnostic precision, potentially leading to increased antibiotic overuse. Our results do not support this conjecture, however. Neither do we find important demand effects after adjusting for GPs' patient mix. In line with the hypothesis about lower transaction and opportunity costs for GPs (Shurtz et al., 2022; Dahlstrand et al., 2025), we find that high-intensity adopters of telemedicine both prescribe less antibiotics and provide more services. Our results are thus consistent with a mechanism where GPs shift some of their activities from prescribing to consultation.

The study closest to ours is Zeltzer et al. (2024), who analyse the impact of increased access to telemedicine in Israel during the COVID-19 pandemic on various outcomes, including antibiotic prescribing. They show that increased access to telemedicine entails an increase in conducted primary care consultations, lower per-visit cost, and fewer prescriptions, and that high-intensity adopters of telemedicine are more likely to have a higher telemedicine utilisation in the post-lockdown period. Our results largely confirm these findings in the Australian context and complement them by studying the diffusion and consolidation of telemedicine use among GPs through a supply-side lens. Understanding the impact of such technology proliferation is particularly important in more choice- and place-based healthcare systems where the supply and range of services may vary substantially across both medical providers and geographical areas (Goetz, 2023).

Our research has important implications for healthcare policy, especially in the key domain of antibiotic prescribing and the global threat of AMR. Since telemedicine has only recently become common in medical practice, the impacts of large-scale rollouts of such technologies are not yet well-known. In particular in countries like Australia with significant urban–rural disparities, telemedicine may provide opportunities for geographically isolated and disadvantaged communities to greatly benefit from improved healthcare access. In addition, our results suggest that telemedicine may have additional benefits as a promising way of mitigating the physician-patient-society agency problem in which primary care providers often give in to patient pressure or practice defensive medicine to prescribe antibiotics inappropriately despite its harmful public health impact. Funding decisions by healthcare policy-makers at all levels of government crucially rely on the capability of telemedicine services to balance access, quality, and efficiency tradeoffs. In this regard, our findings are reassuring in that the use of telemedicine technology in primary care seems to have limited negative impacts on quality whilst providing additional benefits beyond improving access to healthcare.

2. Background and institutional setting

2.1. The Australian healthcare system

The Australian healthcare system is mainly tax-funded and ranks above average among OECD countries in terms of translating health spending into better access, quality, and health outcomes (OECD, 2021). The public healthcare system, known as Medicare, provides free or subsidised access to essential medical services for citizens and permanent residents. Primary care operates on a fee-for-service basis, with services and subsidies set by the government in the Medicare Benefits Schedule (MBS). Subsidies are typically paid directly to healthcare providers, although patients can opt for reimbursement. Providers may choose to accept the subsidy as full payment, known as bulk-billing, or charge above the subsidy, resulting in out-of-pocket costs for patients. GPs are generally not restricted in their location of practice,[6] and patients are free to choose their GP irrespective of where they live. While patients are typically required to register when they first visit a new provider, they are allowed to be registered at multiple[7] providers simultaneously (Wright et al., 2018).

Prescription drugs are similarly subsidised through the Pharmaceutical Benefits Scheme (PBS), with the government negotiating prices with pharmaceutical companies. Patients are required to make a copayment for each prescription, with the amount set by the government and adjusted annually. Those with a concession card, including pensioners or individuals eligible for certain government income support payments, pay reduced copayments. Treatment in public hospitals is fully covered by Medicare for all Australian residents. Privately insured individuals may additionally receive treatment in private hospitals and, depending on the policy, subsidised services for a range out-of-hospital services not covered by Medicare (e.g., physiotherapy, dental services, and optometrics).

Fig. 1 shows that the rate of antibiotic use in Australia is high relative to other OECD countries, with over 40 percent of the population receiving at least one antibiotic prescription per year (ACSQHC, 2019). GPs in Australia prescribe antibiotics for acute respiratory infections at rates that are four to nine times higher than those recommended by clinical guidelines (McCullough et al., 2017). In response to these challenges, the Australian government has implemented strategies to combat AMR through establishing monitoring systems, promoting stewardship practices, and raising stakeholder awareness (Australian Government, 2019).

2.2. Introduction of subsidised telemedicine services

Similar to many other countries, the emergence of the COVID-19 pandemic at the beginning of 2020 prompted Australian authorities to implement a range of suppression and mitigation strategies, including border closures and stay-at-home orders. Although medical care was generally exempt from mobility restrictions, the COVID-19 National Health Plan was created as a response to the challenges facing the healthcare system. Prior to the COVID-19 pandemic, telemedicine in Australia was only available in a very limited capacity.[8] However, due to the nationwide lockdown in March 2020, the federal government rapidly expanded Medicare-subsidised telemedicine services to facilitate patient access to primary care services.[9]

The new rules for telemedicine services allowed GPs, as well as other medical practitioners,[10] to conduct subsidised remote consultations via phone or video calls. New telemedicine items, equivalent to the existing face-to-face items, were added to the MBS. Remote consultations were given separate MBS item codes but shared the same Medicare subsidy. For GPs, services provided via telemedicine were initially required to be bulk-billed, but this restriction was lifted one month after the introduction (in April 2020) and remained in place only for concession card holders, children younger than 16 years old, and patients considered to be at high risk of contracting COVID-19. To maintain continuity of care and to prevent agents from taking advantage of the policy in ways that would undermine its intent, GPs could only offer telemedicine services to patients with whom they or another physician in the same practice had engaged in a face-to-face consultation over the past 12 months prior to the telemedicine appointment: the 'established clinical relationship' rule.[11]

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6 An important exception exists for foreign doctors who are restricted by visa requirements to work in remote areas for up to 10 years after entry.

7 An exception exists for MyMedicare enrollees who can only be registered with one provider at a time. MyMedicare is a voluntary patient registration model introduced in 2023 as part of a government effort to improve continuity of care by providing incentives for patients to see the same GP regularly. See https://www.health.gov.au/our-work/mymedicare.

8 The first Australian Government funded telemedicine initiative was introduced in 2006, allowing mainly psychiatrists to conduct remote consultations for mental health support. Subsequently, several initiatives aimed at bridging the gap in healthcare access of patients living in remote and rural communities of Australia were introduced between 2011–2020 (Dykgraaf et al., 2021).

9 See https://www.health.gov.au/resources/publications/covid-19-national-health-plan-primary-care-package-mbs-telehealth-services-and-increased-practice-incentive-payments.

10 Other medical professionals included in the policy were specialist physicians, consultant physicians, nurse practitioners, participating midwives, allied health providers, and dental practitioners.

11 The requirement was designed to limit cost blowouts from the potential for predatory marketing by telemedicine providers and excessive doctor shopping from patients. We study the sensitivity of our main results with respect to the latter in a subsequent robustness analysis. The rule did not apply to some patients, including children under the age of 12 months; people who are homeless; patients receiving an urgent after-hours service; patients of medical practitioners at an Aboriginal Medical Service or an Aboriginal Community Controlled Health Service; people living in an area declared as a natural disaster area by a State or Territory Government; or people isolating or in quarantine because of a COVID-related State or Territory public health order. See https://www.health.gov.au/resources/publications/askmbs-advisory-established-clinical-relationship-requirement-clarification-of-exemptions.

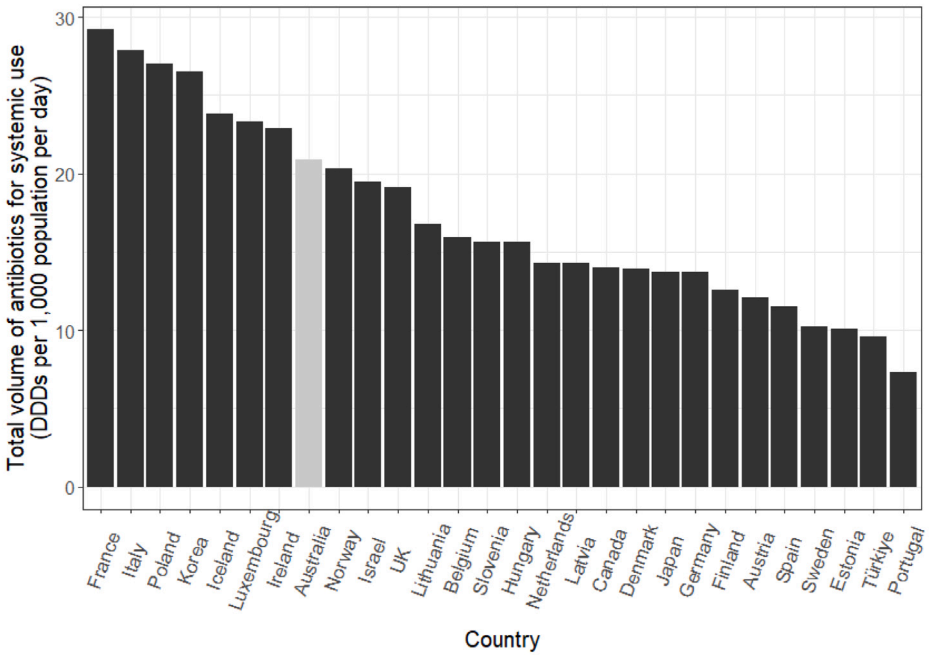

Fig. 1. Total volume of antibiotics for systemic use in OECD countries, 2017.
Note.— OECD healthcare quality and outcomes indicators sourced from https://www.oecd.org/health/health-care-quality-outcomes-indicators.htm. Defined Daily Dose (DDD) is the assumed average maintenance dose per day for a drug used for its main indication in adults. 2017 is chosen as it is the year most OECD countries provided data.

In May 2020, the rollout of electronic prescribing was also fast-tracked[12] to support prescribing from telemedicine consultations. Patients opting for electronic prescriptions would receive a QR code in their phones or emails to present for dispensing at their chosen pharmacy. Some pharmacists offered home delivery to help patients to comply with social distancing rules. By June 2021, over 11 million original and repeat prescriptions had been issued. Electronic prescribing has been adopted by more than 98 percent of pharmacies and by a majority of GPs (ADHA, 2023).

3. Empirical strategy

We employ a difference-in-differences design to study how the rollout of government-subsidised telemedicine services in Australia impacted antibiotic prescribing in primary care. To this end, we first exploit the timing of the introduction of government-subsidised telemedicine services to quantify GPs' intensity of adoption of telemedicine technology. We then apply this measure to compare changes in prescribing outcomes between high- and low-intensity adopters before and after subsidised telemedicine services became available. The main identifying assumption we impose on the data generating process in our causal framework is that the outcomes we study would have followed a common time trend for GPs with different telemedicine adoption intensities in the absence of subsidised telemedicine services.

3.1. Quantifying telemedicine adoption intensity

We quantify GPs' intensity of adopting telemedicine in their patient consultations using a two-level mixed-effects model:

$$TM_{citl} = \alpha + \alpha_l + u_{il} + \delta t + \varepsilon_{citl}, \tag{1}$$

where TM_{citl} is a binary indicator equal to one (zero) if a consultation c by physician i in year-month t and local area l was conducted via telemedicine (face-to-face). Furthermore, we define $\alpha_{il} = \alpha+\alpha_l+u_{il}$ as a composite intercept for physician i practising in local area l, consisting of an overall (fixed) intercept, α, and two stochastic (random) intercepts, $\alpha_l \sim \mathcal{N}(0, \sigma^2_{\alpha_l})$ and $u_{il} \sim \mathcal{N}(0, \sigma^2_{u_{il}})$, respectively. The latter two components capture the relative use of telemedicine in local area l compared to other areas, and physician i's relative use of telemedicine compared to other physicians within l, respectively. The parameter δ captures a common linear time trend in telemedicine use among GPs. Finally, ε_{citl} is a stochastic error term.

[12] See https://www.health.gov.au/resources/publications/covid-19-national-health-plan-primary-care-fast-track-electronic-prescribing.

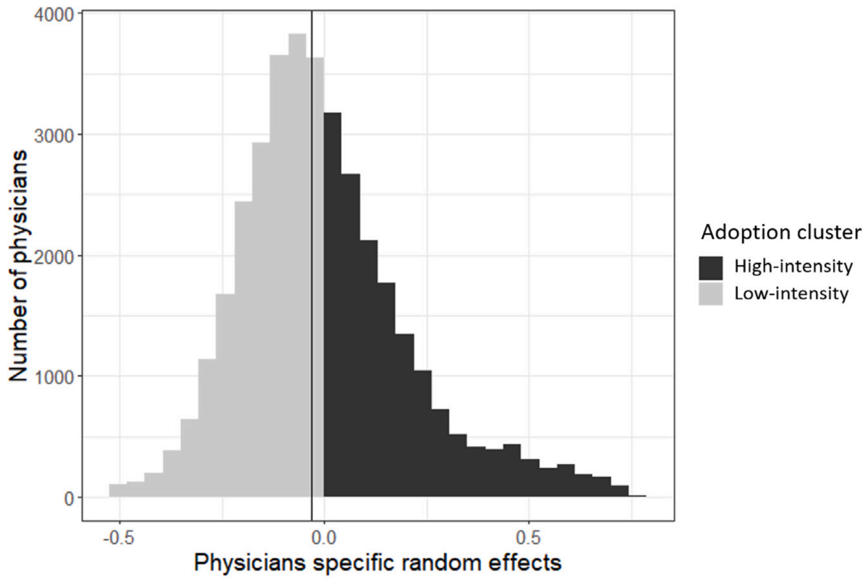

Fig. 2. Distribution of physician-specific random effects in the sample.
NOTE.— Data from the Person Level Integrated Data Asset (PLIDA) and based on the physician sample defined in Section 4. Empirical distribution of physician random effects (u_{il}) from estimation of Eq. (1) in Section 3.1. Physicians with positive (negative) values of $\hat{u}_{il}$ are assigned to the high (low) intensity adoption group.

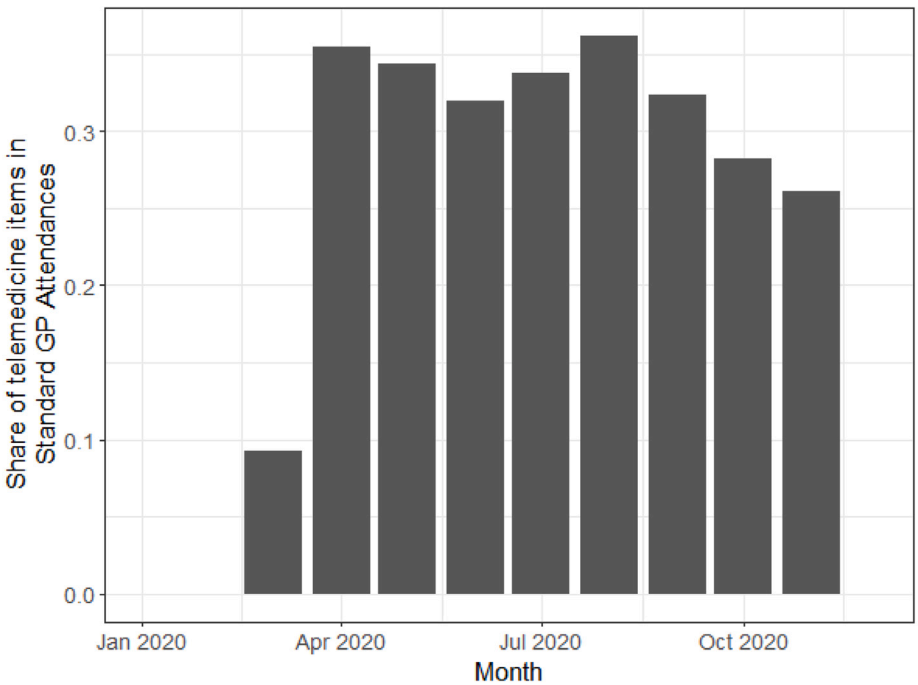

Fig. 3. Share of telemedicine items in all Medicare-subsidised GP consultations in Australia, 2020.
NOTE.— Australian Medicare item reports data sourced from http://medicarestatistics.humanservices.gov.au/statistics/mbs_item.jsp. See Table A2 for definitions of the Medicare items used in the chart.

The model accounts for certain types of unobserved endogeneity arising from variation in patient composition and other area-specific confounding factors, captured by the area-specific intercepts, $\widehat{\alpha}_l$. The estimated physician-specific intercepts, $\widehat{u}_{il}$, are used to assign GPs to telemedicine adoption groups. Specifically, positive values of $\widehat{u}_{il}$ (i.e., physicians with *higher* than average use rates of

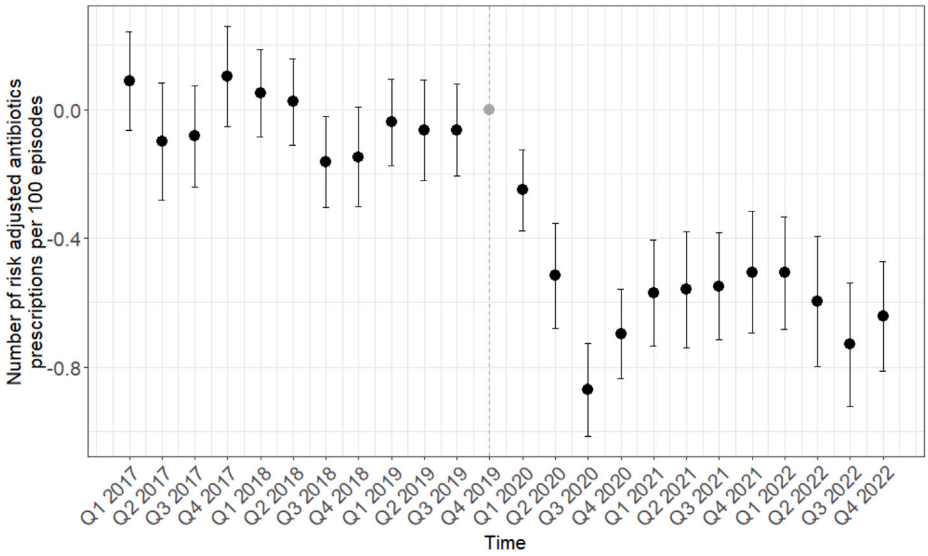

Fig. 4. Event study estimates on relative risk-adjusted GP antibiotic prescribing rates by telemedicine adoption group.
NOTE.— Data from the Person Level Integrated Data Asset (PLIDA) and based on the physician sample defined in Section 4. Circles and associated vertical lines refer to coefficient estimates and 95% confidence intervals based on SA4 region cluster-robust standard errors of τ_t (period-specific differences in outcome between high- and low-intensity adopters of telemedicine) from estimation of Eq. (4) in Section 3.2, respectively. High (low) intensity adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of Eq. (1) in Section 3.1. The dashed vertical line indicates the baseline indexed quarter in the empirical specification.

telemedicine for consultations among all GPs practising in their local area) are assigned to a ***high***-intensity adoption group, while negative values (i.e., physicians with *lower* than average use rates of telemedicine for consultations among all GPs practising in their local area) are assigned to a *low*-intensity adoption group. We designate group membership by:

$$g(i) = \mathbb{1}_{u_{il}>0}. \tag{2}$$

Fig. 2 plots the resulting distributions of $\hat{u}_{il}$ and $\hat{g}(i)$ using our estimation sample described in Section 4.[13]

3.2. Modelling the impact of telemedicine on antibiotic prescribing behaviour

To study whether high- and low-intensity adopters of telemedicine changed their antibiotic prescribing behaviours differently after subsidised telemedicine services were introduced, we estimate the following difference-in-differences model:

$$y_{iq} = \tau \left(post_q \times g(i)\right) + v_i + \lambda_q + \epsilon_{iq}, \tag{3}$$

where v_i and λ_q are physician and year-quarter fixed effects, capturing unobserved heterogeneity (e.g., prescribing preferences) across physicians and over time, and $post_q$ is an indicator variable equal to one for periods after Medicare-subsidised telemedicine services were introduced.[14] τ is the difference-in-differences estimator, measuring the relative change in the outcome (e.g., antibiotic prescribing rate) for high-intensity telemedicine adopters between pre- and the post-telemedicine periods compared with low-intensity adopters. We report standard errors that account for within-area clustering throughout the analysis.[15]

To study the common trend identifying assumption between high- and low-intensity telemedicine adopters, we estimate event study versions of Eq. (3):

$$y_{iq} = \sum_s \tau_s \left(\mathbb{1}_{s=q} \times g(i)\right) + v_i + \lambda_q + \eta_{iq}, \tag{4}$$

[13] Figure A.1 in the Online Appendix plots the raw distribution of telemedicine adoption intensity for the physicians in our sample. Since the distribution is multimodal at the extremes, while the random effects model posits a normal distribution, we conducted robustness checks by re-estimating our models separately for extreme (those with 0 and 100 percent adoption) and non-extreme adopters (everyone else). We discuss results from these modifications in Section 5.3 below.

[14] The inclusion of fixed effects in the model implies that the group-specific indicators $g(i)$ and $post$ will drop out as they are perfectly collinear with the fixed effects.

[15] To account for sampling variation in the estimation of the physician-specific intercepts and for potential error clustering in the difference-in-differences model (Bertrand et al., 2004), we also estimate bootstrapped standard errors by jointly re-estimating Eqs. (1)–(3) using 200 replications with replacement. These estimates are similar to the analytical standard errors.

where s indicates the number of year-quarters from the start of our analysis window. In addition to providing informal evidence on the validity of our empirical approach, the event study specification also allows us to study treatment effect dynamics over both the short and the long term.

4. Data

We use Australian longitudinal register data from the Person Level Integrated Data Asset (PLIDA) to estimate our models. PLIDA combines granular information on health, education, government payments, income and taxation, employment, and demographics for the entire Australian population over time. The primary dataset we use in our analysis consists of data covering the universe of health services and medications reimbursed under Medicare between 2017 and 2022. Each entry in our dataset contains detailed information about provided medical services or prescriptions in the form of unique patient and provider identifiers, date of visit, and specific item numbers based on the MBS and PBS classifications, respectively.

4.1. Sampling

Using the MBS records from PLIDA, we first select all GPs that conducted at least one consultation during the second and third quarter of 2020. Due to the resulting large dispersion and potential outlier influence, we trim the GP sample by excluding the top and bottom five percentiles of physicians with respect to the total number of consultations they conducted across the two quarters. We also exclude GPs based in remote and very remote areas, defined by the Australian Statistical Geography Standard (ASGS) Remoteness Structure, as they were eligible to provide Medicare-subsidised telemedicine services prior to March 2020.[16] Our final estimation sample consists of 36,669 GPs in 103 local areas, with an average of 356 physicians per area.[17,18]

4.2. Medicare items

We base our analysis on the four categories of Medicare-subsidised GP consultations between January 2017 and December 2022, defined as level A, B, C, and D professional attendances.[19] The different categories reflect increasing complexity of the patient's health status and expected time needed to assess and manage the condition, ranging from six minutes for a level A consultation to more than 40 min for a level D consultation. An important feature of the data when mapping corresponding service modalities over time is that each face-to-face item was assigned a 1:1 matching telemedicine item when the latter was added to the MBS in March 2020.[20] Fig. 3 reveals that subsidised telemedicine appointments made up roughly 35 percent of all GP consultations one month after they were introduced and remained high thereafter.[21]

The PBS records included in our analysis contain information on the date of prescription and a unique drug number that can be linked to the Anatomical Therapeutic Chemical (ATC) classification. We identify antibiotic prescriptions as all PBS items within the three-digit ATC class *J01: Antibacterials for systemic use*.[22] The PBS data does not include information on prices or the manufacturer of the prescribed drugs.

4.3. Outcome variables

The main outcome in our empirical analysis is GPs' antibiotic prescription rates, which we model in different ways to account for potential confounding bias. The first and most straightforward definition is the number of antibiotic scripts prescribed by each GP divided by their total number of consultations in a given year-quarter. Since different GP consultation levels vary considerably in duration, we also compute an 'intensive' margin of prescribing: the quarterly number of antibiotic scripts divided by the estimated total minutes of all GP consultations. Total minutes are calculated by summing the weighted average consultation time of each of the four MBS attendance levels using weights from Britt et al. (2002). Using the estimated total duration spent consulting patients,

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16 We use the ASGC's Statistical Area Level 4 (SA4s) in our analysis. There are 108 SA4s that cover the whole of Australia without gaps or overlaps. Most SA4s have a population of between 100,000 and 500,000 people.

17 See the Online Appendix for a detailed explanation on how the analysis sample is constructed.

18 PLIDA contains no personal information on the GPs. We complement our analysis using rich survey data from a representative sample of GPs participating in the Medicine in Australia: Balancing Employment and Life (MABEL) longitudinal survey of doctors. The results, including a validation analysis comparing MABEL and PLIDA data, can be found in the Online Appendix. Similar to the findings of Zeltzer et al. (2024), we find that high-intensity adopters are more likely to be female and younger. High-intensity telemedicine adopters are also more likely to have graduated from a medical school in Australia, to agree or strongly agree that the majority of their patients have complex health and social problems, and to use telemedicine in the post-telemedicine period.

19 Professional attendance is the formal term for a GP consultation in the Australian Medicare system. In the 2020–21 financial year, almost 70 percent of Medicare-subsidised primary care services were comprised by the four attendance levels: see https://www.aihw.gov.au/reports/primary-health-care/general-practice-allied-health-primary-care.

20 Table A.1 and Table A.2 in the Online Appendix provides a detailed description of the different attendance levels and associated Medicare benefit and the cross-walk between face-to-face and telemedicine items (video and phone) for all four attendance levels used in the analysis, respectively.

21 Figure A.2 shows the first-time usage of telemedicine for our sample of physicians. More than 90 percent of GPs conducted their first telemedicine appointment within one month after government-subsidised telemedicine services were introduced.

22 See Table A.3 in the Online Appendix for details on the classification of antibiotics used in the analysis. Combining the MBS and PBS data, we can calculate raw probabilities that face-to-face and telemedicine appointments yield antibiotic prescriptions. Figure A.3 presents raw antibiotic prescription rates for face-to-face and telemedicine appointments by quarter. Face-to-face consultations generally have higher antibiotic prescribing rates throughout our study period.

instead of the total number of consultations, allows us to tackle empirical issues arising from compositional changes in consultation types, which may be conflated with changes in prescribing rates.

To account for endogenous demand-side responses, including correlations in patient preferences for telemedicine providers and for antibiotics, we further modify our definition of the rate of antibiotic prescribing by constructing a case-mix adjusted measure of each GP's patient population with respect to their antibiotic consumption history. To this end, we first derive the list of all unique patients who visited a given GP in our sample at least once during the pre-pandemic period between 2013 and 2018. Next, we compute each patient's total consumption of antibiotics over the same period and standardise the resulting count variable across all patients. Finally, we aggregate this variable to the physician level and include it in our regression models to adjust for patient case-mix variation in antibiotic use across GPs in our sample.

We also modify our measure of antibiotic prescribing rates to account for the possibility that high-intensity adopters of telemedicine may be more likely to schedule a follow-up appointment after an initial consultation to provide the antibiotic prescription. This practice would lead us to falsely interpret a relatively lower antibiotic prescribing rate for high-intensity adopters as a reduction in the probability of prescribing antibiotics for a given patient. To avoid such conflation, we construct a new 'episode' definition of GP consultations that bundles all consultations occurring within a seven day period from the initial consultations for the same patient–physician pair.

To assess quality of prescribing, we analyse guideline-adherent prescribing behaviour within the subgroup of antibiotics for Respiratory Tract Infections (RTIs). Since RTIs are predominantly viral in nature, antibiotics are not effective and should hence not be routinely prescribed for this patient group.[23] Furthermore, to study whether GPs have lower diagnostic capability in virtual consultation settings, we analyse the relative use of broad-spectrum antibiotics for RTI treatment. Broad-spectrum antibiotics are more suitable when the physician is unsure about the patient's condition, while narrow-spectrum antibiotics are used for targeted treatments when the underlying condition has been diagnosed.[24] Current guidelines on antimicrobial resistance recommend to minimise the spectrum of prescribed antibiotics whenever possible (PHE, 2021). We hypothesise that GPs consulting patients via telemedicine might be tempted to prescribe broad-spectrum antibiotics to improve the likelihood of providing effective treatment at the cost of targeting a broader spectrum of microorganisms.[25]

5. Results

In this section we present results from estimation of our models. We first report difference-in-differences estimates for changes in antibiotic prescription rates by comparing high- and low-intensity adopters of telemedicine before and after the introduction of government-subsidised telemedicine services in Australia. We then assess whether these changes improved GPs' guideline-concordant antibiotic prescribing behaviour for RTIs. Finally, we study competing explanations for our results, including demand-side responses from patients and the number of consultations per patient episode, and a set of robustness checks of our empirical specification.

5.1. Does telemedicine affect antibiotic prescription rates?

Fig. 4 plots quarterly coefficient estimates and 95 percent confidence intervals of τ_t from estimation of the event study model defined in Eq. (4). The dependent variable is the rate of antibiotic scripts per 100 Medicare-subsidised GP consultations adjusted for GPs' patient case-mix with respect to their antibiotic drug consumption history. Plotted coefficients are interpreted as year-quarter percentage point changes in relative antibiotic prescribing rates of high- and low-intensity adopters of telemedicine indexed by the last quarter of 2019.

The figure illustrates several interesting findings: First, the estimated coefficients for all time periods up until the first quarter of 2020, when Medicare-subsidised telemedicine services were introduced, are close to zero and do not follow a systematic trend.[26] This empirical pattern is reassuring as it suggests that high- and low-intensity telemedicine adopters did not diverge in their antibiotic prescribing behaviour in the lead-up to the change in policy. Moreover, the figure exhibits a sharp drop in the relative prescribing rate of antibiotics after Medicare-subsidised telemedicine services were introduced.[27] The coefficient pattern suggests a gradual rebound in the relative prescribing rate between the groups in early 2021, followed by a stabilisation and finally a subsequent,

[23] Current Australian guidelines recommend against prescribing antibiotics for upper RTIs: https://www.choosingwisely.org.au/recommendations/asid3. We focus on RTI-related prescriptions as they represent the canonical case of low-value antibiotic prescribing. Other conditions, including urinary tract infections (UTIs), have clearer diagnostic pathways and standardised treatment protocols (Baillie et al., 2024).

[24] See Gillies et al. (2022) for a list of antibiotics prescribed predominantly for RTI, and Coenen et al. (2007) for definitions of broad- and narrow-spectrum antibiotics.

[25] Ideally, we would like to estimate diagnosis-specific antibiotic prescribing rates to elicit the propensity to prescribe given a diagnosed condition. However, our data does not contain information on reported diagnosis for prescribed medications. Moreover, we know of no comprehensive dictionary of all antibiotic spectrum that would allow us to add information about the general use of broad-spectrum antibiotics in a straightforward way. As a result, our findings on prescribing quality should be interpreted with some caution.

[26] A joint test of all pre-trend coefficients fail to reject the null hypothesis of parallel pre-trends for conventional levels of statistical significance. Furthermore, we have tested for linear violations of parallel trends as proposed by Roth (2022) and used the bounding approach by Rambachan and Roth (2023) to analyse the robustness to such violations. Specifically, our difference-in-difference estimate is robust to allowing for violations of parallel trends up to twice as big as a linear violation of the parallel trends assumption in the pre-treatment period that a pre-trends test would detect 80 percent of the time (i.e., a power of 0.8).

[27] Note that the introduction of Medicare-subsidised telemedicine services occurred in March 2020 and hence the coefficient estimate from the first quarter of 2020 is dominated by data from the period before such services were available.

smaller, drop towards the end of 2022. Hence, the lower rate of antibiotic prescribing for high-intensity telemedicine adopters persisted into the post-pandemic period.[28,29]

Our main regression results, based on the difference-in-differences model defined in Eq. (3), are presented in Table 1. Each panel in the table refers to a different set of outcomes. The 'unadjusted' and 'risk-adjusted' columns pertain to specifications without and with adjustment for the GPs' patient population's antibiotic drug consumption history, respectively. The first row of Panel A reports the 'first stage' estimate of τ for the telemedicine consultation rate, showing that high-intensity adopters were on average 14 percentage points more likely to use telemedicine when consulting patients.[30] The second row of the same panel reports corresponding estimates for the relative change in the absolute number of antibiotic prescriptions between high- and low-intensity telemedicine adopters. The result suggest that high-intensity adopters prescribe on average around one (one percent) less antibiotic script per quarter than low-intensity adopters in the post-telemedicine period.

Panel B-D of Table 1 report results for the rate of antibiotic prescriptions using alternative measures for the denominator to ascertain that our results are not attributable to changes in the intensity or composition of consultation types across GP types. Specifically, panel B, C, and D uses the number of GP consultations, the number of care episodes (i.e., bundling all consultations within seven days of the initial appointment), and the total number of consultation hours (estimated using weights from Britt et al., 2002), respectively. The numerator is the same in all models.

The estimation results reveal that the antibiotic prescribing rate was relatively lower for high-intensity telemedicine adopters for all three measures, with magnitudes ranging from three to five percent. The result in panel B mirrors the event study results from Fig. 4, with a relative drop by around 0.6 percentage points for high-intensity adopters in both specifications. This estimate is marginally lower for the episode definition in panel C due to that the number of care episodes, in contrast to the number of consultations, does not increase, suggesting that high-intensity telemedicine adopters increased the number of follow-up appointments they scheduled with patients relative to low-intensity adopters. Finally, the results reported in panel D show that high-intensity adopters significantly reduced their relative antibiotic prescription rates by, on average, 0.02 scripts per hour of consultation. The relative increase in total duration is statistically significant, but the smaller percentage drop in the prescribing rate suggests that the relative change in total duration is less pronounced than the corresponding change in the number of consultations from panel B. Hence, the estimated reduction in relative antibiotic prescribing rate for high-intensity adopters is robust to the choice of denominator, although some of the effect can be attributed to a substitution of shorter, follow-up, consultations for longer ones.[31]

Panel E of Table 1 reports estimates for the share of antibiotics for RTIs to study changes in adherence to prescribing guidelines between high- and low-intensity telemedicine adopters. To this end, we study three related outcomes: the proportion of RTI antibiotics among all prescribed antibiotics, the proportion of RTI broad-spectrum antibiotics among all prescribed RTI antibiotics, and the proportion of RTI broad-spectrum antibiotics among all prescribed antibiotics. The former outcome gauges whether high-intensity adopters' prescribing aligns more or less with the recommendation to not routinely prescribe antibiotics for RTIs, while the two latter outcomes are informative of the extent to which high- and low-intensity adopters differ in terms of the recommendation to minimise the spectrum of prescribed antibiotics whenever possible. The estimation results suggest that high-intensity telemedicine adopters behave slightly more guideline-concordant in terms of prescribing antibiotics for RTIs, but are also somewhat more likely to prescribe broad-spectrum antibiotics. While precisely estimated, these estimates do not indicate economically important changes in the use of antibiotics for RTIs between the two telemedicine adoption groups.

5.2. Are effects supply- or demand-driven?

Our results so far suggest that GPs who adopted telemedicine more intensively reduced their antibiotic prescribing rates relative to less intense adopters without impacting their adherence to RTI prescribing guidelines. One interpretation of these findings is that telemedicine is a more efficient medium to conduct medical consultations in primary care. This may be due to one or a combination of the hypotheses outlined in the introduction, including lower transaction and opportunity costs of GPs' time, and an environment where patient pressure to prescribe antibiotics when unwarranted is less obtrusive for the physician. However, there exists other competing mechanisms that could generate similar results. Importantly, while we include local area fixed effects in our models, these parameters do not control for time-varying sorting of patients to high- and low-intensity adopters of telemedicine *within* areas.

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28 Similarly, Figure A.4 in the Online Appendix shows that high-intensity adopters of telemedicine consistently retained a relatively higher share of telemedicine consultations throughout the analysis period.

29 The pre-period in Fig. 4 also provides us with a useful test of whether high- and low-intensity adopters were likely to act differently during infectious disease outbreaks in Australia. Specifically, recent influenza outbreaks occurred in the third quarter of 2017 and the second quarter of 2019 (Muscatello et al., 2021). If high-intensity telemedicine adopters are likely to respond differently to disease outbreaks, such as COVID-19, we should have also observed noticeable impacts during these influenza epidemics. However, we see no differential behaviour of high- and low-intensity telemedicine adopters during these events.

30 This estimate corresponds closely to the coefficient pattern in Figure A.4 in the Online Appendix where we also explore geographical variation in telemedicine adoption across Australia. The richness of spatial and temporal variation in our data allows us to compare the impacts of state government COVID-19 policy (comparing local areas with similar mobility changes *across* states) and COVID-19 induced mobility changes (comparing local areas with different mobility changes *within* states). Our results suggest that government intervention, to a greater extent than reductions in community mobility, played a central role in the intensity of telemedicine adoption of GPs and that this initial diffusion wave led to persistent variations in the application of telemedicine technology across Australia.

31 Linearly extrapolating the difference in telemedicine use between high- and low-intensity adopters reported in panel one of Table 1 suggests that a one percentage point change in telemedicine uptake corresponds to around 0.04 fewer antibiotics prescriptions per 100 consultations, or by four scripts (34 percent reduction) for a hypothetical GP who fully adopts telemedicine in their practice.

Table 1
Difference-in-differences estimates on antibiotic prescriptions and GP telemedicine adoption intensity.

	Unadjusted			Risk-adjusted		
Dependent variable	Mean	$\hat{\tau}$	Δ	Mean	$\hat{\tau}$	Δ
Panel A: Telemedicine consultations and number of antibiotic prescriptions						
Telemedicine consultation rate	0.032	0.144*** (0.004)		0.032	0.143*** (0.004)	
Number of antibiotic prescriptions	102.6	−1.118* (0.660)	−1%	102.6	−1.172* (0.662)	−1%
Panel B: Antibiotic prescriptions per 100 consultations						
Antibiotic prescription rate	11.99	−0.562*** (0.057)	−5%	11.99	−0.625*** (0.058)	−5%
Number of GP consultations	816.2	9.627** (3.729)	1%	816.2	10.76*** (3.745)	1%
Panel C: Antibiotic prescriptions per 100 care episodes						
Antibiotic prescription rate	12.90	−0.495*** (0.060)	−4%	12.90	−0.564*** (0.061)	−4%
Number of care episodes	750.3	−0.709 (3.234)	0%	750.3	0.455 (3.244)	0%
Panel D: Antibiotic prescriptions per consultation hour						
Antibiotic prescription rate	0.467	−0.013*** (0.002)	−3%	0.467	−0.016*** (0.002)	−3%
Total consultation duration	208.3	1.919** (0.802)	1%	208.3	2.107*** (0.802)	1%
Panel E: Antibiotic shares for respiratory tract infections (RTI)						
RTI antibiotics	0.557	−0.006*** (0.001)	−1%	0.557	−0.006*** (0.001)	−1%
RTI-BS in RTI antibiotics	0.570	0.006*** (0.002)	1%	0.570	0.006*** (0.002)	1%
RTI-BS in all antibiotics	0.374	0.002 (0.001)	1%	0.374	0.002 (0.001)	1%
Panel F: Patient composition and consultation intensity						
Risk adjustment index	0.450	0.026*** (0.001)	6%			
Consultations per episode	1.073	0.017*** (0.001)	2%	1.073	0.017*** (0.001)	2%
Number of observations	672,536			672,536		

Note.— Data from the Person Level Integrated Data Asset (PLIDA) and based on the physician sample defined in Section 4. Reported coefficients and SA4 region cluster-robust standard errors refer to estimates of τ (difference in outcome between high- and low-intensity adopters of telemedicine) from estimation of Eq. (3) in Section 3.2, respectively. High (low) intensity adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of Eq. (1) in Section 3.1. Means are based on outcome averages in 2019 across all sampled physicians and Δ refers to the difference between the outcome-specific coefficient estimate $\hat{\tau}$ and the reported mean. RTI and RTI-BS antibiotics refer to Respiratory Tract Infection antibiotics and Respiratory Tract Infection Broad-spectrum antibiotics, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 2
Difference-in-difference estimates from varying sample and model specification.

	(1) Main specification	(2) Established relationship	(3) Donut exclusion	(4) Continuous treatment	(5) Fixed effects	(6) Extreme adopters	(7) Non-extreme adopters
Antibiotic prescriptions per 100...							
consultations	−0.562***	−0.463***	−0.639***	−2.010***	−0.789***	−1.881***	−0.607***
	(0.057)	(0.049)	(0.060)	(0.171)	(0.069)	(0.549)	(0.056)
	[0.041]	[0.042]	[0.041]	[0.106]			
episodes	−0.495***	−0.391***	−0.566***	−1.882***	−0.701***	−1.706***	−0.543***
	(0.060)	(0.065)	(0.063)	(0.162)	(0.068)	(0.558)	(0.059)
	[0.043]	[0.053]	[0.043]	[0.112]			
risk-adjusted consultations	−0.625***	−0.508***	−0.701***	−1.946***	−0.858***	−1.647***	−0.543***
	(0.058)	(0.048)	(0.062)	(0.179)	(0.070)	(0.541)	(0.055)
	[0.040]	[0.041]	[0.041]	[0.107]			
risk-adjusted episodes	−0.564***	−0.443***	−0.641***	−1.710***	−0.775***	−1.454***	−0.477***
	(0.061)	(0.064)	(0.064)	(0.170)	(0.070)	(0.550)	(0.058)
	[0.043]	[0.053]	[0.043]	[0.113]			
Number of observations	672,536	570,861	596,904	672,536	672,536	20,347	652,189

Note.— Data from the Person Level Integrated Data Asset (PLIDA) and based on the physician sample defined in Section 4. Reported coefficients and SA4 region cluster-robust analytical and bootstrapped standard errors (200 replications with replacement) in parentheses and square brackets refer to estimates of τ (difference in outcome between high- and low-intensity adopters of telemedicine) from estimation of Eq. (3) in Section 3.2, respectively. High (low) intensity adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of Eq. (1) in Section 3.1. Rows refer to number of antibiotics prescriptions per 100 consultations (first row); number of antibiotics prescriptions per 100 episodes (second row); number of risk adjusted antibiotics prescriptions per 100 consultations (third row); and number of risk adjusted antibiotics prescriptions per 100 episodes (fourth row). Models refer to our main results from Table 1 (column 1); excluding all patient–physician pairs that did not have at least one GP consultation in the previous year (column 2); excluding physicians with estimated propensity to adopt telemedicine between 45th and 55th percentile (column 3); replacing the binary definition of adoption intensity with a continuous representation using the raw uptake estimate (column 4); estimating propensity to adopt telemedicine using a fixed-effects, instead of a mixed-effects, model (column 5); and partitioning the sample into groups of 'extreme' (column 6) and 'non-extreme' (column 7) adopters using the raw distribution of telemedicine uptake from Figure A.1 in the Online Appendix. Extreme is defined as having a telemedicine share of zero or one, while non-extreme includes everyone else. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Such endogeneity could arise if healthier patients who are seeking care for medical conditions that do not require antibiotics are more likely to request telemedicine consultations.

We deal with this issue using our case-mix adjusted measure of each GP's patient population with respect to their antibiotic drug consumption history as explained in Section 4. The 'risk-adjusted' column in Table 1 pertains to estimates where we control for each GP's patient case-mix. Point estimates from the unadjusted and risk-adjusted specifications are similar and never statistically distinguishable. However, the slightly larger point estimates for the risk-adjusted model suggest some positive sorting of healthier patients to high-intensity telemedicine adopters. Furthermore, the first row of Panel F reports the estimate from using the risk-adjustment index as an outcome in our difference-in-differences model. The positive and significant estimate corroborates the positive sorting hypothesis that high-intensity adopters attract patients with on average higher antibiotic consumption rates. However, the selection is not strong enough to qualitatively alter the interpretation of our main findings.

Another potential confounding factor in our analysis is related to the increase in the relative number of GP consultations among high-intensity adopters of telemedicine. This could be spuriously interpreted as an increase in the probability of prescribing antibiotics if telemedicine consultations are, on average, more likely to prompt follow-up consultations. This could occur if the initial remote consultation is intended to screen patients for a potential face-to-face appointment which would be incorrectly interpreted as a reduction in the rate of antibiotic prescriptions.[32]

To study the sensitivity of our results to consultation inflation from follow-up appointments, we apply our episode definition from Panel C of Table 1 and re-estimate our model using this definition as outcome. The last row of Table 1 reports the results from this exercise. The positive and statistically significant estimate indicates that high-intensity adopters of telemedicine are more likely to schedule a follow-up appointment after an initial consultation. However, the difference is small and replacing the consultation definition with the episode definition for our main outcomes in Panel C only marginally changes the magnitude of the point estimates.[33]

5.3. Robustness checks

Table 2 presents the results from a set of sensitivity checks with respect to sample and model specification. Each row in the table pertains to one of the four different definitions of the antibiotic prescribing rate: non-adjusted scripts per 100 GP consultations, non-adjusted scripts per 100 episodes, risk-adjusted scripts per 100 GP consultations and risk-adjusted scripts per 100 episodes. In addition, alongside the area-clustered standard errors (parentheses), we also include bootstrapped standard errors using 200 replications with replacement (brackets) for our results where feasible. The magnitude of the latter estimates are comparable to the former in all instances.

Column (1) of the table replicates our main results from Table 1 for comparison. In column (2), we study whether the established clinical relationship rule for telemedicine appointments alters our estimates by excluding all patient–physician pairs that did not have at least one GP consultation in the previous year. The remaining sample is hence eligible for telemedicine services with their registered GP and therefore not restricted to an initial face-to-face appointment. In column (3), we exclude GPs with estimated random effects between the 45th and 55th percentiles from our adoption model specified in Eq. (1) to avoid misclassifying borderline physicians as high- or low-intensity adopters due to sampling errors. Estimates from this model also provide a more clear-cut comparison of the two groups with more pronounced telemedicine preferences. Column (4) shows results from replacing the binary definition of adoption intensity with a continuous representation using the raw uptake estimate. Column (5) reports results from applying an alternative approach to estimating physician telemedicine adoption propensity by including physician fixed-effects and controlling for patients' characteristics, including gender and age, and our risk-adjustment index. This specification is comparable to the model used in Zeltzer et al. (2024) and useful as a comparison. Finally, the last two columns report estimates from partitioning the sample into groups of 'extreme' and 'non-extreme' adopters using the raw distribution of telemedicine uptake from Figure A.1 in the Online Appendix. Extreme is defined as having a telemedicine share of zero or one, while non-extreme includes everyone else.

Aside from some variation in coefficient magnitudes, our main results reported in Table 1 are generally robust to all model modifications. The slightly attenuated estimate for the established clinical relationship sample is possibly due to that these patients already have an ongoing relationship with their doctor and are less likely to be 'shopping' for antibiotics. Moreover, the higher estimates for the continuous treatment and extreme adopters is consistent with a monotonic dose–response mechanism where a higher telemedicine share of a GP monotonically decreases the probability of prescribing antibiotics, since the estimated coefficient is interpreted as a change from zero to one telemedicine share in both cases. Estimates from remaining specifications are similar in magnitude to our main results reported in column (1).

[32] Follow-up consultations may also be used as a way for the physician to delay prescribing of antibiotics whereby the GP asks the patient to return if symptoms do not resolve within a specified time frame. However, a more common practice is that the GP issues the prescription in the initial consultation and asks the patient to wait before using it (Spurling et al., 2023).

[33] Figure A.5 and Figure A.6 in the Online Appendix display event studies for four different definitions of the antibiotic prescribing rate. Models are separated by whether they include patient risk-adjustment (or not) and whether they specify a consultation or an episode definition. The results are robust to the choice of rate definition.

6. Conclusions

This paper investigates whether use of telemedicine in primary care consultation affects the quality of prescribing antibiotics among general practitioners (GPs) in Australia. We exploit a nationwide policy where government-subsidised telemedicine services were introduced to alleviate loss of access to healthcare precipitated by the COVID-19 pandemic. Our analysis uses Australian longitudinal register data to quantify relative antibiotic prescription rates for physicians who varied in their intensity to adopt telemedicine in their patient consultations after such services were made available.

Our study draws several conclusions: First, high-intensity adopters of telemedicine reduced their antibiotic prescribing rates relative to low-intensity adopters. While we are unable to identify exact mechanisms, our results are consistent with previous evidence showing that GPs feel more pressure from patients to prescribe antibiotics when not clinically indicated in face-to-face settings. Moreover, part of the effect we estimate is attributed to an increase in consultation frequency, suggesting that more efficient time use may have led GPs to reduce reliance on antibiotics as substitute for limited consultation time. Second, we find no empirical support for that high-intensity adopters of telemedicine are less adherent to guidelines due to lower diagnostic capability. Third, results are persistent over time and carries over into the post-pandemic period, suggesting that GPs' practice styles may have been permanently altered. Finally, demand-side factors, including patient–physician sorting or doctor-shopping, appear unlikely to be important in explaining our findings.

In contrast to many innovations in healthcare, the technological barriers to market entry for telemedicine are minimal. However, video and phone appointments are not perfect substitutes for face-to-face consultations and telemedicine limits the scope of conducting detailed physical examinations. Hence, clinicians may face more challenges in diagnosing and treating patients in other areas of care than those studied in this paper. While the context of antibiotic prescribing is important due to its public health impact on antimicrobial resistance, future research could focus on other clinical settings to provide a fuller picture of the benefits and disadvantages of telemedicine.

CRediT authorship contribution statement

Daniel Avdic: Writing – review & editing, Writing – original draft, Project administration, Methodology, Formal analysis, Conceptualization. **Johannes S. Kunz:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Susan J. Méndez:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Conceptualization. **Maria Wiśniewska:** Writing – review & editing, Writing – original draft, Investigation, Formal analysis, Data curation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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The results of these studies are based, in part, on data supplied to the ABS under the Taxation Administration Act 1953, A New Tax System (Australian Business Number) Act 1999, Australian Border Force Act 2015, Social Security (Administration) Act 1999, A New Tax System (Family Assistance) (Administration) Act 1999, Paid Parental Leave Act 2010 and/or the Student Assistance Act 1973. Such data may only used for the purpose of administering the Census and Statistics Act 1905 or performance of functions of the ABS as set out in section 6 of the Australian Bureau of Statistics Act 1975. No individual information collected under the Census and Statistics Act 1905 is provided back to custodians for administrative or regulatory purposes. Any discussion of data limitations or weaknesses is in the context of using the data for statistical purposes and is not related to the ability of the data to support the Australian Taxation Office, Australian Business Register, Department of Social Services and/or Department of Home Affairs' core operational requirements.

Legislative requirements to ensure privacy and secrecy of these data have been followed. For access to PLIDA and/or BLADE data under Section 16A of the ABS Act 1975 or enabled by section 15 of the Census and Statistics (Information Release and Access) Determination 2018, source data are de-identified and so data about specific individuals has not been viewed in conducting this analysis. In accordance with the Census and Statistics Act 1905, results have been treated where necessary to ensure that they are not likely to enable identification of a particular person or organisation.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jhealeco.2025.103096.

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