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Discussion Paper no. 2024-09

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JEL Classification: H41, I11, I13, O33

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Does telemedicine affect prescribing quality in primary care?*

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June 17, 2024

Abstract

We study how the diffusion of telemedicine technology impacted the quality and rates of antibiotic prescriptions using Australian survey data from primary care physicians linked to administrative records on their service provision. We classify physicians based on their relative use of telemedicine consultations in response to the introduction of government-subsidised telemedicine during the COVID-19 pandemic and relate their rates of antibiotic prescriptions to indicators of prescribing quality before and after lockdown periods in a difference-in-differences design. Our results suggest that more frequent users of telemedicine prescribe relatively fewer antibiotics while keeping prescribing quality largely unchanged. We interpret these findings as evidence that telemedicine can enhance efficiency of service provision in primary care settings.

JEL-codes: H41, I11, I13, O33
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*We thank Line Björnskov Pedersen, Anthony Harris, Carol Propper, Anthony Scott, and seminar participants at the 1st Economics of the Healthcare Workforce Workshop, Monash University, 44th Australian Health Economics Association Conference, Asian and Australasian Society of Labour Economics 2023 Conference (Taipei), 2023 Monash Addiction Research Centre Symposium, Workshop on Accessibility and Affordability of Healthcare, Workshop of Applied Economics in Digital Health (Potsdam), and 6th Swiss Health Economics Workshop for valuable comments. Funding by the Australian Research Council (DP220103306) is gratefully acknowledged. All remaining errors are our own.

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1 Introduction

Technologies that improve the efficiency of healthcare delivery are in high demand due to rapidly increasing costs of healthcare. One such innovation that has recently gained considerable attention is telemedicine, which provides digital healthcare services remotely via video or telephone. The main appeal of telemedicine, or telehealth[1], is that it can reduce physical and financial barriers to accessing healthcare services that prevent individuals from receiving the care they need and are entitled to (Berman and Fenaughty, 2005) and improve matching between patients and providers (Dahlstrand, 2022). However, although most researchers agree 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 may compromise the quality of care from lower diagnostic performance compared with in-person consultations (Willis et al., 2021).

In this paper, we exploit a natural experiment to study the effects of rolling out nationwide telemedicine services in Australia on the quality and costs of prescribing pharmaceuticals among primary care physicians. We focus on the important case of antibiotics which, while crucial for treating many life-threatening bacterial infections, are also considered harmful due to their negative externalities in the form of accelerated antimicrobial resistance (Adda, 2020).[2] Since telemedicine represents a significant shift in how medical care is delivered, we hypothesise that the factors that influence doctors in their decisions to prescribe antibiotics to patients may be altered in two distinct ways when they transition from in-person to telemedicine consultations. First, the increased physical remoteness between physician and patient may reduce the

[1] Telehealth and telemedicine are often used interchangeably. However, they are not the same. While 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 more narrowly defined as the *practice of medicine* using remote means (e.g., diagnosing and treating patients). While the difference between these two concepts is not crucial for the motivation or context of our paper, we will nevertheless primarily use telemedicine throughout the paper to avoid any confusion.

[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 antimicrobial resistance (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

emotional pressure that the latter is able to exert on the former. This may *decrease* the intensity of inappropriate antibiotic prescriptions if physicians are prone to decide against their own judgement for financial or other reasons (Scott et al., 2022). Second, the increased distance may impede a physician's ability to conduct a satisfactory diagnosis of their patient's health status. This may *increase* the intensity of inappropriate antibiotic prescriptions if risk-averse physician decides to err on the side of caution (Miller, 2003). As a result, the theoretical effect of telemedicine vis-à-vis in-person consultations on primary care physicians' prescribing quality is ambiguous and must be studied empirically.

The empirical framework we employ in our analysis is based on the Australian federal government's responses to the COVID-19 pandemic, together with institutional and epidemiological features of Australia's governance structure and geography. 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.[3] Since the use of telemedicine in primary care was essentially non-existent prior to this date, we leverage this unique setting in a difference-in-differences empirical design by comparing changes in antibiotic prescription rates of physicians who were relatively fast and slow in adopting telemedicine for standard patient consultations, respectively, after such services became available. Furthermore, the varying government responses and epidemiological contexts to the COVID-19 pandemic on the state level, ranging from a maximum suppression strategy with strict lockdown policies to near business as usual, present an excellent opportunity to study the mechanisms and factors underlying the diffusion of telemedicine services and their consequences for health policy. To account for patient selection and other unobserved heterogeneity, we compare changes in outcomes between the pre-pandemic period at the end of 2019 and the period of relative COVID-19 abatement at the end of 2020 for physicians practising within the same local administrative area.

We use physician-level panel data based on comprehensive survey data on a sam-

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

ple of general practitioners (GPs) obtained from the Medicine in Australia: Balancing Employment and Life (MABEL) survey, linked to administrative records on consultations and prescribed pharmaceuticals from the Australian Medicare Benefits Schedule (MBS) and the Pharmaceutical Benefits Scheme (PBS). We use this information to first estimate the physician-specific propensity of telemedicine uptake during the first nationwide COVID-19 lockdown period in Australia. Next, we use the estimated telemedicine propensity to study the association between the rate of telemedicine adoption and relative changes in antibiotic prescription rates before and after the first COVID-19 lockdown. Finally, we exploit regional variation on the intensity of COVID-19 impacts across Australia for a series of policy-relevant extensions to our main analysis to investigate associations between physician-specific characteristics, telemedicine adoption, and prescribing efficiency.

Our main finding suggests that faster telemedicine uptake among GPs is associated with lower rates of antibiotic prescriptions. Specifically, our results show that the rate of antibiotic prescriptions per standard patient consultation dropped 10 percent more for GPs who were above the average adoption rate of telemedicine consultations (fast adopters) relative to GPs who were below the average adoption rate (slow adopters) in the last quarter of 2020 compared to the same quarter in 2019. This difference is explained by both a relative increase in the number of consultations (6%), and a relative decrease in the total number of prescribed antibiotic scripts for fast adopters (-4%). These results hence lend some support for the hypothesis that telemedicine technology could reduce the emotional pressure put on GPs when interacting with patients who demand antibiotics in cases when such treatment modalities are unjustified.

To study whether the reduction in antibiotic prescription rates among fast adopters was associated with changes in prescribing quality, we further analyse the relative use of broad and narrow-spectrum antibiotics for respiratory tract infections (RTIs) as proxy variables for low- and high-value care, respectively. Our estimation results indicate a statistically and economically significant reduction of (low-value) broad spectrum antibiotic prescriptions among RTI patients by fast telemedicine adopters relative to slow adopters (-5%). This finding suggests that the hypothesis that physical remoteness of telemedicine impairs GPs' ability to diagnose patients and leads them to prescribe inappropriate antibiotics is unlikely to persist in our data. Furthermore, estimating the impact of telemedicine on costs, we find a small, but statistically insignificant, increase in the difference between the average total fees charged by fast and slow adopters (2%), respectively. However, breaking down this total cost increase into public (Medicare) and private (out-of-pocket) expenditures, we find that it is entirely derived from government subsidies (4%), hence implying that patients' out-of-pocket costs indeed decreased on average.

We also use the rich information from the MABEL survey to analyse the characteristics of fast- and slow adopters of telemedicine in order to inform about which factors are predictive of telemedicine use among GPs. We find that fast adopters of telemedicine are more likely to be younger, female and graduates from Australian medical schools. In addition, fast adopters have on average greater shares of patients with complex health and social problems, illustrating the importance of access to healthcare for fragile and disadvantaged groups (Scott et al., 2021). Interestingly, we find no statistically significant differences between fast and slow adopters in terms of (big five) personality traits, locus of control or risk preferences. Moreover, we find no important differences in tech-savviness between the two groups with respect to their stated attitude to and adeptness in using digital health technologies, although this analysis is based on a smaller sample with little variation in the outcome variable.

Since changes in the intensity of prescribing of antibiotics may be endogenously driven by changes in patient composition based on demand for telemedicine, we also conduct a placebo test using GPs prescription shares for chronic conditions under the assumption that any changes in this share would indicate a change in patient composition. We motivate this argument by that chronic patients are unlikely to suddenly change their treatment regimen, so any observed variation in prescriptions for chronic patients over time should primarily reflect a change in the GPs patient mix. Reassuringly, we do not find any evidence that the relative shares of scripts for chronic conditions between slow and fast adopters of telemedicine changed during the period we study.

Finally, we explore the underlying relationship between antibiotic prescription rates and geographical variation in telemedicine adoption through two separate but related channels: state variation in government COVID-19 responses and variation in community mobility changes. The rich degree of spatial and temporal variation in our data allows us to employ a difference-in-differences design to compare both the impacts of government policy (comparing local areas with similar mobility changes *across* states) and 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 uptake of telemedicine among GPs. Although this government-induced proliferation of telemedicine technology did not appear to lead to lower antibiotic prescription rates, as evidenced by that antibiotic prescriptions by fast adopters decreased relatively more in states with laxer government COVID-19 responses, it seemed to have increased prescribing quality in terms of a significant drop in the prescribing of broad-spectrum antibiotic scripts.

Our paper contributes to the growing set of studies that analyse the relationship between the use of telemedicine and quality of care (Shi et al., 2018; Ray et al., 2019; Knies, 2024). For example, Ray et al. (2019) examine claims data from a private insurance scheme in the US, finding that paediatric patients with acute respiratory infections are more likely to receive antibiotic prescriptions in a telemedicine setting and that telemedicine visits are less likely to elicit guideline-concordant antibiotic management. Our results are partly contrasting these findings in that we find reductions in the use of antibiotics in telemedicine settings and no indications of lower quality of prescribing. One reason for the diverging findings could be that our analysis capture results from a broader and more general population group as we focus on healthcare provided in an universal public health insurance setting.

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 visits, lower per-visit cost, and fewer prescriptions, and that fast adopters of telemedicine are more likely to be female, younger, and have a higher telemedicine utilisation in the post-lockdown period. Our results confirm these findings in the Australian context. Moreover, we complement these findings using the unique Australian COVID-19 context to analyse the mechanisms underlying the diffusion and consolidation of telemedicine use among primary care providers in greater detail through the supply side lens. Understanding such adoption patterns is particularly important in more choice- and place-based healthcare systems where the supply and range of services provided may vary substantially across both medical practitioners and geographical areas (Goetz, 2023).

Finally, our research also has important implications for healthcare policy. Since the use of telemedicine has only been relevant in the last decade or so, the effects of large-scale rollouts of such technology 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 residents to benefit from improved access to healthcare. Funding decisions of telemedicine by healthcare policymakers on all levels of government crucially relies on the capability of such services to manoeuvre access and efficiency trade-offs. In this regard, our findings are reassuring in that the negative effects of telemedicine in primary care appear to be negligible.

2 Background and institutional setting

2.1 The Australian healthcare system

The Australian healthcare system is tax-funded and largely universal. It 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. They 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 in general not restricted in their location of practice,[4] and patients are free to choose their preferred GP; that is, they are not required to register with a GP in their catchment area or within a specific physician network.

Prescription pharmaceuticals are similarly subsidised through the Pharmaceutical Benefits Scheme (PBS), with the government negotiating prices with pharmaceutical companies. Patients are required to make a co-payment for each prescription, with the amount set by the government and adjusted annually. Those with a concession card, such as pensioners or those on certain government benefits, receive reduced co-payments. Private health insurance does not cover GP consultations outside of hospitals or pharmaceuticals. Treatment in public hospitals is free for patients.

2.2 Introduction of subsidised telemedicine services in Australia

Similar to many other countries, the emergence of the COVID-19 pandemic at the beginning of 2020 prompted Australian authorities to carry out a range of suppression and mitigation strategies, such as border closures and imposing population mobility restrictions. Although medical care was exempted from the mobility restrictions, the COVID-19 National Health Plan was created in parallel as a response to the challenges facing the healthcare system including the management of an unprecedented increase in the volume of ambulance services and hospital admissions as a consequence of rapidly increasing COVID-19 infection rates. Prior to the COVID-19 pandemic, telemedicine in Australia was only available in a very limited capacity.[5] However, in large part

[4] An exception exists for foreign doctors who are restricted by visa requirements to work in remote areas for a number of years.

[5] 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

due to the imposed mobility restrictions and the nationwide COVID-19 lockdown, the federal government opted to rapidly expand Medicare-subsidised telemedicine services to all Australians on 13th March to enable patients to attend medical appointments without having to leave home.[6]

The new rules for telemedicine services allowed GPs (as well as other medical practitioners) to conduct subsidised remote consultations via phone or video conference.[7] New telemedicine items, equivalent to the existing face-to-face items, were added to the MBS. Video and phone 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 ensure certain continuity of care and limit gaming of the system, GPs could only offer telemedicine services to patients with whom they or another doctor in the same practice had had a face-to-face consultation in the past 12 months preceding the telemedicine service appointment. This "established clinical relationship" restriction was implemented throughout the period we study in this paper.[8]

In May 2020, the rollout of electronic prescribing was also fast-tracked[9] as a tool to support prescribing during telemedicine consultations. Patients opting for e-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 with social distancing. By June 2021, almost 11.3 million original and repeat pre-

communities of Australia were introduced between 2011-2020 (Dykgraaf et al., 2021).

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

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

[8]The established relationship requirement did not apply to some patients: 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 due by a State or Territory Government; people isolating or in quarantine because of a COVID-related State or Territory public health order. See https://www.mbsonline.gov.au/internet/mbsonline/publishing.nsf/Content/Factsheet-TempBB.

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

scriptions had been issued. Electronic prescribing had been adopted by more than 98 percent of the pharmacies and by a majority of the GPs (ADHA, 2023).

2.3 Antibiotic prescribing in Australia

Antimicrobial resistance (AMR) is a global concern caused by the overuse and misuse of antibiotics. The consumption of antibiotics is closely linked to AMR, as higher utilisation can lead to decreased effectiveness due to bacteria developing resistance. 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). Figure 1 shows that the use rates of antibiotics in Australia are high relative to other comparable OECD countries. One reason for this is that GPs in Australia prescribe antibiotics for acute respiratory infections at rates that are 4-9 times higher than those recommended by clinical guidelines (McCullough et al., 2017). As a response to these challenges, the Australian government recently implemented strategies to combat AMR by establishing monitoring systems, promoting stewardship practices, and raising awareness (Australian Government, 2019).

The increasing popularity of telemedicine highlights the need for ongoing monitoring and optimisation of antibiotic prescribing practices to ensure responsible use and manage risks associated with AMR effectively. The primary focus of this paper is in studying how the diffusion of telemedicine impacts antibiotic prescription rates due to the unique challenges prescribing GPs are faced with when consulting patients remotely. We consider two hypothetical channels for how telemedicine may impact antibiotic prescribing. First, over-prescribing may occur due to the reduced capacity of the consulting physician to conduct in-depth, independent patient examinations (Huang and Ullrich, 2024). GPs may prescribe antibiotics as a precautionary measure, rather than based on a definitive diagnosis when they are not able to perform a physical examination (Scott et al., 2022). On the other hand, physicians may also prescribe antibiotics too generously in face-to-face contexts due to real or perceived patient pressure (Macfarlane et al., 1997; Hoffmann and Del Mar, 2015). In a remote setting, physicians might feel more confident in overruling patients' preferences in favour of clinical guidelines on AMR (van De Pol et al., 2021), thus reducing the rate of antibiotic prescribing. Therefore, whether increased use of telemedicine among GPs is likely to increase or decrease antibiotic prescribing is ambiguous and must be studied empirically.

3 Empirical strategy

We apply a difference-in-differences methodology to study how the introduction of subsidised telemedicine services in Australia impacted antibiotic prescription rates and quality in primary care. To this end, we first exploit the timing of the introduction of government-subsidised telemedicine services to quantify GPs' speed of adoption of telemedicine technology. We subsequently use the adoption measure to compare changes in various outcomes across physicians before and after the first COVID-19 lockdown in Australia. 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 who were fast and slow in adopting telemedicine in the absence of the introduction of subsidised telemedicine services.

3.1 Quantifying the speed of telemedicine adoption

We first quantify GPs' speed of adoption of telemedicine technology by estimation of a two-level hierarchical mixed-effects model:

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

where TM_{citl} is defined by a binary indicator equal to one (zero) if a GP attendance c by physician i in year-month t and local area l was conducted via telemedicine (face-to-face). Furthermore, 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) components, $\alpha_l \sim \mathcal{N}(0, \sigma^2_{\alpha_l})$ and $u_{il} \sim \mathcal{N}(0, \sigma^2_{u_{il}})$, respectively. The latter two components capture the relative area-specific use of telemedicine in local area l, and physician i's relative use of telemedicine within local area l, respectively. The parameter δ captures a linear secular time trend in telemedicine uptake across all physicians and local areas. Finally, ε_{citl} is a random regression error orthogonal to the other regressors and model parameters.

By modelling physicians to be nested within local areas, our approach 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, α_l. The estimated physician-specific intercepts are used to assign each physician in our sample into groups of either fast or slow telemedicine adopters based on the sign of u_{il}. Specifically, positive values of u_{il} (i.e., physicians with *higher* than average use rates of telemedicine in their patient attendances among all physicians practising in their local area) are assigned to the group of fast adopters, while negative values (i.e., physicians with *lower* than average use rates of telemedicine in their patient attendances among all physicians practising in their local area) are assigned to the group of slow adopters. We define the following variable to specify group membership:

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

Figure 2 plots the resulting distributions of u_{il} and $g(i)$, respectively, using our estimation sample described in Section 4 below.

3.2 Modelling the effect of telemedicine on antibiotic prescribing behaviour

To study whether physicians who were slow and fast in adopting telemedicine behaved differently with respect to their antibiotic prescribing behaviour, we estimate the following difference-in-differences model:

$$y_{it} = \beta_0 + \beta_1 post_t + \tau\,(post_t \times g(i)) + v_i + \epsilon_{it}, \tag{3}$$

where v_i are physician fixed effects[10], capturing individual unobserved heterogeneity across physicians, and $post_t$ is an indicator variable for the post-lockdown period (relative to the pre-lockdown period; see details in the next section). The difference-in-differences estimator, τ, measuring the relative change in y_{cit} (e.g., antibiotic prescription rate) for fast telemedicine adopters across pre- and the post-lockdown periods compared to slow adopters, is the key model parameter of interest, ϵ_{it} is an error term.[11]

To study the identifying assumption of common time trends between fast and slow telemedicine adopters, we also estimate event study versions of equation (3) through estimation of

$$y_{it} = \beta_0 + \sum_t \tau_t \left(\mathbb{1}_{T=t} \times g(i) \right) + v_i + \lambda_t + \epsilon_{it}, \tag{4}$$

where t are quarterly time periods between January 2018 and December 2020 and λ_t are quarter fixed effects. In addition to providing further insights on treatment effect dynamics, the event study specification allows us to study the common trend assumption to assess the validity of our causal framework.

4 Data and sampling

We use data from the Medicine in Australia: Balancing Employment and Life (MABEL) longitudinal survey of doctors to estimate our models. The survey was conducted annually between 2008 and 2018, covering approximately 10,000 medical practitioners (including 3,500 GPs) each year and includes detailed information on the physician's age, education, family situation, work hours, and practice characteristics, as well as validated measures of risk aversion, personality, and attitudes towards digital medicine prior to the COVID-19 outbreak. MABEL respondents are representative of the physi-

[10]The inclusion of physician fixed effects in the model implies that the group-specific indicator $g(i)$ will drop out if included as it is perfectly co-linear with the fixed effects. Hence, it is omitted from equation (3).

[11]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 in all models by re-estimating equations (1)-(3) using 1,000 replications with replacement. These estimates are very similar to the analytical standard errors reported in the result section and are available from the authors upon request.

cian population in Australia (Szawlowski et al., 2020). In our analyses, we focus on the subset of 1,099 GPs in MABEL who also consented to link their survey responses with Medicare records from Medicare Benefits Schedule (MBS) and Pharmaceutical Benefits Scheme (PBS) between October 2011 and December 2020. Specifically, the administrative data contains all service and prescription records reported to Medicare for each included GP. The data does not contain information on individual patients.

We further restrict our GP sample for reasons relating to the feasibility in estimation of our empirical model. First, we keep only GPs who conducted a minimum of 100 and a maximum of 5,500 standard GP consultations between April and September 2020 to reduce bias from measurement errors and extreme outliers. Moreover, we drop GPs based in remote and very remote areas, as defined by the Australian Statistical Geography Standard (ASGS) Remoteness Structure, as they were eligible to provide Medicare-funded telemedicine services prior to March 2020. Finally, since we apply area-level fixed effects in our empirical analysis, we exclude geographic areas with only one physician from our sample.[12] Our final estimation sample consists of 632 GPs.

The medical services we base our analysis on comprise the four main categories of GP consultations, defined in the MBS system as level A, B, C, and D standard GP attendances.[13] The categories are ranked in descending alphabetical order, indicating increasing complexity of the patient's medical condition and expected time required to assess and manage the condition.[14] We use data on GP consultations provided between January 2018 and December 2020 in our analysis. An important feature of the data when mapping corresponding telemedicine and face-to-face service types is that each face-to-face consultation item was assigned a 1:1 matching telemedicine item when telemedicine was introduced as MBS items in March 2020.[15] Applying the face-

[12] We use ASGC's Statistical Area Level 4 (SA4s) as our preferred geographic area. There are 108 SA4s covering the whole of Australia without gaps or overlaps. Most SA4s have a population of between 100,000 and 500,000 people.

[13] In the 2020-21 financial year, almost 70 percent of Medicare subsidised primary care services was comprised by the four types of GP consultations: see https://www.aihw.gov.au/reports/primary-health-care/general-practice-allied-health-primary-care.

[14] Table A.1 provides a detailed description of the different categories.

[15] Table A.2 reports the crosswalk between face-to-face and telemedicine items (video and phone) for all four consultation types we use in our analysis.

to-face-telemedicine crosswalk to national Medicare statistics in Figure 3, we see that telemedicine consultations made up roughly 35 percent of GP attendances in Australia one month after its introduction and remained high thereafter.[16]

The PBS records we include in our analysis provide information about date of prescription and a unique PBS number for each drug linked to the Anatomical Therapeutic Chemical (ATC) classification. We identify antibiotic prescriptions in our data as all PBS items matched within the three-digit ATC class *J01: Antibacterials for systemic use*. The data does not include information on prices paid by patients or the manufacturer of prescribed drugs.

The main outcome of interest in our empirical analysis is GPs' antibiotic prescription rates, which we model in two different ways. The first and most straightforward definition we use is the number of antibiotic scripts prescribed by each GP divided by their total number of consultations in a given year-quarter. However, since the consultations we consider may vary considerably in duration, we also compute an 'intensive' margin definition of prescription rates, obtained by dividing the quarterly number of antibiotic scripts by the estimated total minutes of all standard GP attendances. The denominator is constructed by summing the weighted average consultation time in each of the four levels of GP consultations using weights derived in Britt et al. (2002). Importantly, using the total duration spent consulting patients, 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 prescription rates.

To assess the quality of prescribing, we consider two separate indirect tests. First, we analyse prescription rates within the subgroup of broad and narrow antibiotics for respiratory tract infections (RTIs). Broad-spectrum antibiotics are more suitable as a treatment for an RTI when the physician is unable to diagnose the condition of the patient, while narrow-spectrum antibiotics are used in more targeted treatments

[16] Figure A.1 shows the first-time usage of telemedicine for our sample of physicians. Over 90 percent of GPs conducted their first telemedicine consultation within one month from the introduction of government-funded telemedicine services.

when the underlying condition is known.[17,18] Current guidelines on antimicrobial resistance recommend to minimise the spectrum of prescribed antibiotics whenever possible (PHE, 2021). Given this, we hypothesise that GPs consulting patients via telemedicine might be tempted to prescribe broad-spectrum antibiotics to improve the probability of providing an effective treatment at the cost of targeting a broader spectrum of microorganisms in cases where they are unable to identify a precise patient diagnosis.

Second, we contrast the change in the rate of prescribed antibiotics with total acute conditions prescriptions, defined as all non-chronic medications as described in Purkiss et al. (2020). This measure allows us to study changes in prescription composition across patients with non-chronic conditions. Specifically, we hypothesise that telemedicine visits might elicit relatively more antibiotic prescriptions among patients with acute conditions by inappropriately diagnosing viral infections as bacterial. Hence, relative increases in the use of broad-spectrum RTI-related antibiotics or in the general use of antibiotics among acute conditions medications by the GPs with higher shares of telemedicine appointments may indicate that telemedicine induces lower diagnostic capability.

Finally, in order to evaluate changes in patient composition or increases in unnecessary visits across GPs in our sample, we study chronic conditions scripts, again using the definition in Purkiss et al. (2020). We hypothesise that dispensing of such drugs should not change significantly over time, since patients suffering from chronic diseases need to medicate indefinitely on a regular basis. Therefore, finding differences in the share of chronic condition scripts prescribed by slow and fast adopters of telemedicine over time may indicate changes in relative patient compositions across the two groups.

Table 1 reports sample summary statistics of baseline physician characteristics broken down into categories of fast and slow adopters of telemedicine, respectively. In terms of clinical characteristics, we see that fast adopters are significantly different from slow adopters in several dimensions. Similarly to the findings of Zeltzer et al.

[17]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.

[18]See Table A.3 for details on the classification of antibiotics used in the analysis.

(2024), fast adopters are more likely to be female and younger. Fast 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-adaptation period. With regard to other characteristics, including being part of the senior staff in practice, practice size, and preferences for risk-taking, we do not find any important baseline differences across groups.

The MABEL survey also includes information on personality traits and locus of control (internal and external), which we study in the two middle panels of Table 1. In terms of the Big 5 personality traits (openness, conscientiousness, extroversion, agreeableness, and neuroticism), we find that fast adopters of telemedicine have on average a higher degree of openness, conscientiousness, extroversion and neuroticism, but lower degree of agreeableness, than slow adopters. Fast adopters are also more likely to have a higher internal locus of control, although none of these differences are statistically significant at conventional levels.

Lastly, the bottom panel of the table summarises physicians' approach towards digital health, studied in the last wave of MABEL survey collected in 2018. Across all assessed aspects, we observe no significant differences between fast and slow adopters. It is important to note, however, that these questions were only included in one survey wave and resulted in a small sample size, hence they should be interpreted with caution.[19]

5 Results

In this section we present our results from estimation of our models. We first report difference-in-differences estimates for changes in antibiotic prescription rates by comparing fast and slow adopters of telemedicine before and after COVID-19 lockdowns in Australia. We then assess whether these changes improved efficiency by analysing

[19] Figure A.2 shows regression estimates from a model regressing the telemedicine adopter indicator variable on each of the variables listed in Table 1 to adjust for any covariance between factors. Results remain largely the same, both qualitatively and quantitatively.

the costs and quality of changes in antibiotic prescriptions. Finally, we study whether these changes were likely to be driven by supply or demand factors by comparing changes in GPs prescription shares for chronic conditions.

5.1 Does telemedicine affect antibiotic prescription rates?

Figure 4 illustrates quarter-specific coefficient estimates and 95 percent confidence intervals of τ_t from estimating the event study model defined in equation (4) for the rate of antibiotic scripts per 100 Medicare-subsidised standard GP attendances. Plotted coefficients are thus interpreted as year-quarter percentage point changes in relative antibiotic prescribing rates of fast and slow adopters of telemedicine compared to the reference point in the last quarter of 2019.

The figure illustrates several interesting findings: First, the estimated coefficients for all time periods up until the second quarter of 2020, when Medicare-subsidised telemedicine services were introduced, are insignificant and close to zero. This pattern is reassuring for our empirical approach as it suggests that fast and slow telemedicine adopters did not diverge in their antibiotic prescribing behaviour in the lead-up to the policy change. Moreover, the figure exhibits a sharp drop in the relative prescription rate of antibiotics after Medicare-funded telemedicine professional GP attendances were introduced. In other words, fast adopters of telemedicine were relatively less likely than slow adopters to prescribe antibiotics to their patients after telemedicine items were introduced as billable Medicare items. Finally, the coefficient estimates for the last quarter in the figure remain negative and statistically significant, suggesting that the relative reduction in antibiotics prescribed by fast adopters of telemedicine remained even after the COVID-19 lockdown period in 2020 ended.

Our main regression results, based on the difference-in-differences model defined in equation (3), are presented in Table 2. For this model we only use data from the last quarters of 2019 and 2020 (i.e., the pre- and post-lockdown periods, respectively). Each panel in the table refers to a different set of outcomes. Starting with Panel A, the first row reports estimates of τ for the relative change in the rate of antibiotic prescriptions per 100 GP attendances (i.e., the same outcome as in Figure 4). In line with the event study results, we find a relative drop in the rate of antibiotics prescribed by fast adopters by -1.5 percentage points, or 10 percent. The next two rows report separate estimates for the nominator (number of antibiotic scripts) and denominator (number of GP attendances) of the constructed prescribing rate variable. The coefficient estimates reveal that the total number of antibiotic scripts prescribed by fast and slow adopters of telemedicine did not change significantly. Rather, the effect on the prescription rate is mainly driven by an increase in the number of quarterly GP attendances by 40, or six percent, among fast adopters.

Panel B of Table 2 shows results using an alternative measure to estimate the effect of telemedicine uptake on the rate of antibiotic prescriptions; namely, the total time (in hours) GPs spend with patients in their attendances. This is done to account for the fact that estimated changes in the number of GP attendances could simply be due to changes in the composition of standard attendances (i.e., types A, B, C, and D) across GP types, without necessarily affecting the total duration of time with patients (if shorter attendance types are substituted for longer ones). Using this alternative rate measure, we see from the first row in the second panel of the table that fast adopters of telemedicine significantly reduced their relative antibiotic prescription rates by, on average, -0.05 scripts per hour of attendance. This estimate implies a nine percent drop in prescribed antibiotics relative to the baseline in the last quarter of 2019, similar to the percentage effect reported in the first row of Panel A. The third row of Panel B shows that this result is partially driven by a relative increase of eight attendance hours per quarter, or four percent, for fast adopters of telemedicine. Hence, the estimated reduction in the relative rate of antibiotic prescriptions is robust to the choice of denominator and mainly mediated through the intensive margin.

5.2 Impacts on prescription costs and quality

The results from the first two panels of Table 2 suggest that GP service provision increased among fast, relative to slow, adopters of telemedicine. Therefore, another relevant outcome to study is the extent to which corresponding costs of GP attendances changed between the two groups. The first and second rows of Panel C in Table 2 report difference-in-differences estimates of the relative change in the total quarterly fee revenue and total quarterly Medicare benefit paid for the GP attendances included in our sample, respectively. While both point estimates are positive, the total fee revenue only increased by two percent on average. Since the corresponding total benefit increased by four percent, this means that the relative out-of-pocket cost actually decreased for patients who visited fast adopters of telemedicine.[20]

Panel D of Table 2 reports estimates for two quality indicators of antibiotic prescribing practice: antibiotic scripts as a share of all scripts dispensed for acute conditions and the share of broad-spectrum antibiotics in the group of Respiratory Tract Infection (RTI) antibiotics. Holding patient population constant, an increased rate in either of these two outcomes would indicate lower prescribing quality according to current Australian clinical guidelines for antibiotic prescribing (McCullough et al., 2017). While the estimated coefficients for both indicators are negative, only the share of prescribed broad-spectrum antibiotics used for RTIs is associated with a statistically significant reduction; -0.03, or by five percent. This result suggests that, if anything, fast adopters of telemedicine improved the quality of their antibiotic prescribing practice relative to slow adopters. With respect to the hypothesised impact of telemedicine on prescribing quality, our findings hence supports the 'emotional pressure' over the 'diagnostic capability' conjecture, although we cannot directly identify either channel in our data.

5.3 Are effects supply- or demand-driven?

Our main findings thus far suggest that GPs who were relatively fast in adopting telemedicine during the COVID-19 lockdown period reduced their antibiotic prescription rates, spent more time with patients, and prescribed antibiotics more in line with clinical recommendations compared to slower adopters of telemedicine. One inter-

[20]The out-of-pocket cost, or gap payment, is the difference between the physician's fee for a medical service and the Medicare subsidy. This finding is likely to be, at least partly, related to the requirement for GP telemedicine attendances to be bulk-billed (fully covered by Medicare) for some patients and during part of the time period we study.

pretation of these results is that telemedicine is a more efficient medium to conduct medical consultation in primary care. This may be due to the hypothesis we posited in the introduction where a remote consultation setting allows the GP to be less impacted by emotional pressures from patients to prescribe antibiotics against their own professional judgement. However, other competing explanations that would generate similar empirical results might exist. Most pertinently, while we control for local areas fixed effects in all our models, we are unable to adjust for any demand-induced changes in the composition of patients *within* areas over time that choose to attend fast and slow adopters of telemedicine, respectively. For example, if patients who seek help with medical conditions that do not require antibiotics are more likely to attend GPs with higher use rates of telemedicine, our interpretation that the telemedicine modality for medical consultations improves antibiotic prescribing quality would be spurious.[21]

In order to evaluate changes in patient composition or increases in unnecessary visits across GPs in our sample, we study chronic conditions scripts selected using the definition in Purkiss et al. (2020). To conduct this placebo test, we estimate equation (3) for two additional outcomes using the same sample. First, we compute the share of scripts associated with chronic conditions as a fraction of all scripts prescribed by the GPs. This share allows us to assess whether fast telemedicine adopters maintained a steady share of patients with chronic conditions. Finding a significant difference in this outcome would suggest that some patients were purposely selecting GPs based on their consultation modality. Second, we study the absolute number of scripts associated with chronic conditions, which can be interpreted as a proxy for the number of patients with chronic conditions attended by the GP. Similarly, if the composition of patients remained unchanged over time, we would expect a null effect when estimating the model for this outcome.

Our results are presented in the Panel E of Table 2. Reassuringly, we find no

[21]Moreover, the antibiotic-to-consultation ratio might be a reflection of larger unnecessary visits induced by either patients (i.e., uncertainty about potential COVID-19 symptoms) or providers requesting more follow-ups, although Zeltzer et al. (2024) finds evidence against this.

evidence that the relative share of the total number of chronic condition scripts changed between fast and slow adopters of telemedicine after the introduction of government-funded telemedicine services. Given that the share of chronic condition scripts can be considered a reasonable proxy for a GP's share of patients with chronic conditions, we interpret this result as supporting the claim that changes in the composition of patients between the groups of fast and slow adopters of telemedicine were unlikely to be important. This reinforces the interpretation from our main results, presented in panels A-D of Table 2, that the use of telemedicine among GP consultations improved both service accessibility and the quality of antibiotic prescribing in Australia.

6 Which factors contributed to telemedicine diffusion in Australia?

Given that our results suggest that telemedicine adoption benefits health system efficiency by improving both the quantity and quality of (certain) GP services at a moderate increase in cost, we now turn to studying which factors prompted the diffusion of telemedicine services among primary care providers in Australia. We consider two related, but distinct, factors based on the specific Australian setting during the COVID-19 pandemic period: the intensity of COVID-19 induced community mobility changes and the state governments' COVID-19 responses. Both of these factors are likely to have accelerated GPs' transition to telemedicine technology in order to keep their livelihoods in the backdrop of reduced community mobility and Government-provided incentives for telemedicine services. The specific research questions we explore in this context are: (i) did areas with greater COVID-19 community mobility reductions also have more rapid adoption of telemedicine technology among GPs; (ii) were these mobility effects primarily mediated by COVID-19 or through government intervention; and (iii) did the mobility-induced effects impact the quality of antibiotic prescribing differently?

To answer these questions, we construct a new dataset based on local area-level indicators of community mobility and telemedicine utilisation shares. We use publicly available mobility data from Google's COVID-19 Community Mobility Reports to identify reported mobility changes in local areas throughout 2020. We specify a crosswalk to map Google's area identifiers to the SA4 area codes and calculate a mobility indicator as the overall average change in mobility in each SA4 across the three indicators of interest: retail and recreation, transit, and workplace over the selected time periods.[22] To calculate local area-level telemedicine utilisation shares, we use administrative data of all standard GP attendances conducted in 2020 from the Australian Bureau of Statistics (ABS). Finally, we link the aggregated mobility and telemedicine utilisation data on the corresponding area and time levels to enable us to study the relationship between the two factors.

6.1 Community mobility and telemedicine uptake

We first establish whether the community mobility indicator we apply in our analysis is associated with uptake of telemedicine services by local area. Figure 5 displays the spatial distribution of Google's mobility changes in Australia from April to December 2020 relative to the average mobility in January and February of the same year, where darker areas indicate stronger reductions in community mobility. It is clear from the figure that the south-eastern states, Victoria and New South Wales, were more affected than other regions, presumably due to the fact that the COVID-19 pandemic disproportionately affected these areas. In some areas, including greater Melbourne, the aggregate mobility measure indicate a decrease in more than 40 percent on average across the entire 2020.

Figure 6 combines the local area-level community mobility changes and telemedicine shares in a scatter plot to study the association between the two factors. The fitted regression line suggests a strong and precisely estimated linear relationship of almost -1, suggesting a 1:1 relationship between telemedicine uptake and reduction in com-

[22]The mobility data is available from https://www.google.com/covid19/mobility. The data extract consists of estimates of changes in mobility in Local Government Areas (LGAs) on a daily level compared with the pre-lockdown mobility in 2020 for 6 different mobility categories: retail and recreation, grocery and pharmacy, parks, transit, workplace, and residential mobility.

munity mobility. This relationship is fairly constant across the entire mobility change distribution and not impacted by any extreme outlier observations. Hence, relative changes in community mobility seem to have been a key factor for the diffusion of telemedicine technology in Australia.

6.2 Government policy or community isolation?

Since the reductions in community mobility in Australia during 2020 were caused by several factors, including the governments' COVID-19 pandemic response plans (e.g., lockdowns, social distancing and stay-at-home orders), as well as a general concern among citizens to contract the disease, it is not immediately clear which of these factors were more important for the diffusion of telemedicine. Specifically, both self-prescribed isolation among members in a community, as a positive shifter of the demand for telemedicine services, and government policy to encourage the use of remote consultation technology may have incentivized GPs to adopt telemedicine in Australia.

To shed further light on the underlying relationship between telemedicine uptake and community mobility, we utilise the fact that the state of Victoria was subject to considerably stricter COVID-19 restrictions than other Australian states in 2020. Specifically, while a staggered lifting of restrictions occurred across the country after the initial nationwide lockdown at the end of March 2020, a second COVID-19 wave in August in the same year plunged Victoria into another lockdown.[23] Panel (a) and (b) in Figure 7 display time series of mobility changes in the state of Victoria and the rest of Australia in weekly detail, respectively, using our mobility measure. While the first (nationwide) lockdown in April generated comparable mobility responses for both Victoria and the rest of Australia, the second (Victorian) lockdown clearly changed the mobility trajectory for Victorians compared to other states.

We exploit the variation in COVID-19 policy response between Victoria and the rest of Australia to study the association between changes in community mobility

[23] Restrictions included 1.5-meter social distancing, stay-at-home orders, work-from-home directives, industry and school closures, and in the second lockdown in Victoria also a maximum one hour of outdoor exercise daily, travel restrictions to within five km of one's home, and an 8 pm to 5 am curfew.

and telemedicine uptake within and across states in another difference-in-difference design. Our analysis is based on the two most populous states, Victoria (VIC) and New South Wales (NSW), as they share large borders and are comparable in most relevant aspects relative to other states and territories in Australia.[24] Specifically, we use the aggregated mobility and telemedicine MBS data to estimate the following regression model:

$$\begin{aligned} TM_{ls}(t) = \gamma_0 + \gamma_1 VIC_{s(l)} + \\ \gamma_2 lmob_l(t) + \gamma_3 \left(lmob_l(t) \times VIC_{s(l)} \right) + \epsilon_{ls}, \ t \in [t_0, t_1], \end{aligned} \tag{5}$$

where TM_{ls} is the share of standard GP attendances that were conducted using telemedicine in local area l (i.e., SA4) and state s pooled across months in the interval between t_0 and t_1. Similarly, $lmob_l(t)$ and $VIC_{s(l)}$ are dummy indicators for whether the average mobility change in local area l was above the median mobility change (in absolute terms) for all areas between t_0 and t_1, and for whether l is located in the state of Victoria (as opposed to NSW), respectively. The estimated γ parameters will be informative of the extent to which the diffusion of telemedicine was primarily driven by government policy or general COVID-19 community isolation responses by studying each factor while holding the other factor constant.[25]

Table 3 reports estimates of γ_0-γ_3 from equation (5) for different period intervals over the course of 2020. Specifically, column (1) shows point estimates for the entire COVID-19 lockdown period between April and October while column (2) expands the period until December. Columns (3)-(5) show estimates for the first nationwide lockdown in April-May, the second Victorian lockdown in July-October, and the post-lockdown period in November-December, respectively. The constant (γ_0) across all columns is interpreted as the average share of telemedicine attendances in local areas with below median mobility reductions in NSW over the relevant time period, while the

[24]VIC and NSW were also the states with by far the most COVID-19 infections in Australia. The two panels in Figure 8 provide a comparison of the mobility variation for the two states.

[25]For example, the estimate of γ_1 would be interpreted as the partial impact of Victoria, holding community mobility fixed, and the estimate of γ_2 would be interpreted as the partial impact of low community mobility, holding state fixed. Note also that the model in equation (5) is saturated.

row titled 'Victoria' (γ_1) reports the corresponding telemedicine share in Victoria in addition to the NSW share. Likewise, the row titled 'Low mobility' (γ_2) is interpreted as the estimated additional change in the telemedicine share in local areas above median mobility reductions in NSW, and the interaction between the two factors (γ_3) as the corresponding additional share for Victoria, respectively.

The results from the table suggest that, across all time intervals, Victoria had at least a 50 percent higher telemedicine share than NSW. The share was more than 75 percent higher during the Victorian lockdown, as indicated in column (4), and remained significantly higher even after the lockdown ended. In contrast, community mobility changes in isolation seemed to play a relatively minor role for the adoption of telemedicine; areas where the mobility change was above the median mobility change did not have significantly higher telemedicine shares in neither NSW (row two) nor in Victoria (row three) at any point during 2020. We therefore interpret these findings as that the main underlying factor for the rapid uptake of telemedicine in Victoria was associated with the Victorian government's COVID-19 pandemic response.

6.3 Heterogeneous effects on antibiotic prescribing

Given the strict Victorian pandemic response and the findings from the previous subsections, it is reasonable to believe that GPs in Victoria reacted differently relative to GPs in other states and territories. We, therefore, study heterogeneity in the association between telemedicine adoption and antibiotic prescribing rates by estimating our main difference-in-differences model, defined by equation (3), separately for Victoria and for the rest of Australia. The results are reported in Table 4 where the first two sets of columns present estimates for Victoria and the rest of Australia, respectively, while the last column shows results for the difference between the two groups from estimation of a fully interacted triple-difference model with a Victoria dummy indicator as the third factor.

The results displayed in panel A of the table imply that fast adopters of telemedicine in Victoria, on average, reduced their antibiotic prescription shares slightly less (-7%)

than fast adopters in other states (-9%). This difference is mainly caused by the opposite sign on the total number of antibiotic scripts prescribed in Victoria, although almost entirely counteracted by a stronger increase in the total number of attendances. A similar pattern emerges when applying our alternative measure for service provision, shown in panel B. Thus, GPs who were relatively fast in adopting telemedicine in Victoria offered more services than fast adopters in other regions, on average.

In terms of costs, the estimates in panel C show that both total fee revenues and benefits increased relatively more among fast adopters of telemedicine in Victoria compared to the rest of Australia. However, the cost increases are roughly proportional to the relative increase in the number or duration of standard attendances. Furthermore, the quality of antibiotic prescribing significantly improved among fast adopters of telemedicine in Victoria compared to other states and territories. The within-Victoria drop in the prescription share of broad spectrum antibiotics of six percentage points (-9%) is statistically significant, compared to a corresponding near-zero estimate in the rest of Australia. In terms of the impact on chronic conditions, the pattern is more mixed with both a relative increase and a relative decrease in the two outcomes.

We interpret these results as that the impact of telemedicine adoption on the antibiotic prescribing behaviour of GPs in primary care was similar in Victoria compared to the rest of Australia, save for relative increases in total service provision and prescribing quality. Perhaps as a consequence of stricter policy or the overall higher uptake of telemedicine in the state, Victorian GPs who were quicker in adopting telemedicine attendance modalities relative to their local peers offered both relatively more service appointments and aligned their prescribing practice more with current clinical recommendations than similar GPs in other states and territories. This could be an artefact of regulation insofar that it may include greater monitoring to which physicians may have responded even after the Victorian lockdown was lifted, or reflect more intense competition among primary care providers since telemedicine services have the potential to reach more patients than traditional face-to-face visits.

7 Conclusions

This paper investigates whether the use of telemedicine technology in primary care patient consultations affects the quality of prescribing antibiotics among GPs in the Australian primary care system. To this end, we exploit a natural experiment in which government-funded telemedicine services were introduced to counter effects on access from mobility restrictions precipitated by the COVID-19 pandemic. We use detailed data from a representative sample of Australian GPs to study the uptake of telemedicine services for professional attendances and antibiotic prescription rates and quality among physicians who were relatively fast and slow in adopting telemedicine consultations after these services became publicly available.

Our study draws two key conclusions: First, we show evidence of large and persistent variations in the diffusion of telemedicine technology across general practitioners (GPs) in Australia. This suggests that some patients may still face challenges in accessing healthcare services and that direct government intervention might be required to equalise access to telemedicine. Second, we provide evidence that fast adopters of telemedicine were associated with improved prescribing quality, measured as the degree to which prescribing practice aligned with current Australian clinical recommendations. Fast adopters also increased the overall time spent with their patients, without disproportionate increases in patient out-of-pocket expenditures for telemedicine appointments. These effects were more salient in the state of Victoria, where uptake of telemedicine among GPs was extensive due to a more restrictive COVID-19 government response and resulting reductions in community mobility.

While telemedicine is a relatively new innovation in healthcare, the technological and regulatory barriers to market entry are minimal. Indeed, the vast majority of GPs in our sample conducted their first telemedicine consultation within one month from the introduction of government-funded telemedicine services. We find no evidence that increased use of telemedicine in primary care attendances led to adverse effects in the form of lower diagnostic quality. However, video and phone consultations are not perfect substitutes for face-to-face visits and telemedicine settings limit the possibilities of conducting a physical examination. Hence, medical professionals might face more serious challenges in both diagnosing and treating patients in other contexts than those studied in this paper. Further research from other settings is therefore required to provide a fuller picture of the trade-offs involving telemedicine services.

Acknowledgement

Funding from the Australian Research Council DP220103306 is gratefully acknowledged. This research used data from the MABEL longitudinal survey of doctors, the Medicare Benefits Schedule (MBS), and the Pharmaceutical Benefits Scheme (PBS). We acknowledge *Services Australia* as the source of the MBS and PBS data and thank them for their support. Funding for MABEL was provided by the National Health and Medical Research Council (2007 to 2016: 454799 and 1019605); the Australian Department of Health and Ageing (2008); Health Workforce Australia (2013); The University of Melbourne, Medibank Better Health Foundation, the NSW Department of Health, and the Victorian Department of Health and Human Services (2017); and the Australian Government Department of Health, the Australian Digital Health Agency, and the Victorian Department of Health and Human Services (2018). The study was approved by The University of Melbourne Faculty of Business and Economics Human Ethics Advisory Group (Ref. 0709559) and the Monash University Standing Committee on Ethics in Research Involving Humans (Ref: 195535 CF07/1102 – 2007000291). The MABEL research team bears no responsibility for how the data has been analysed, used or summarised in this research.

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.

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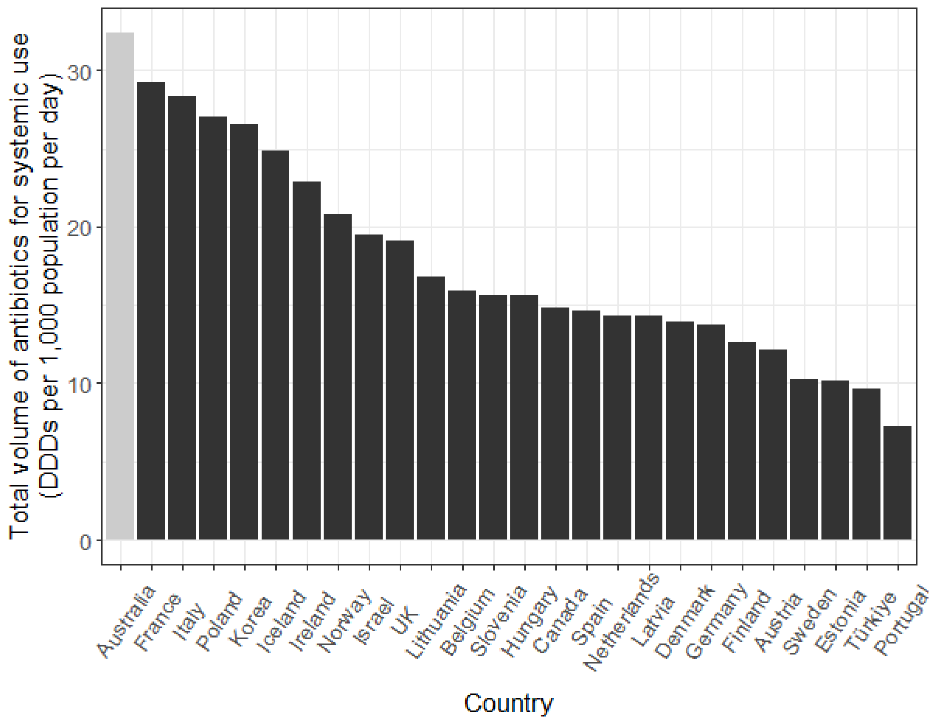
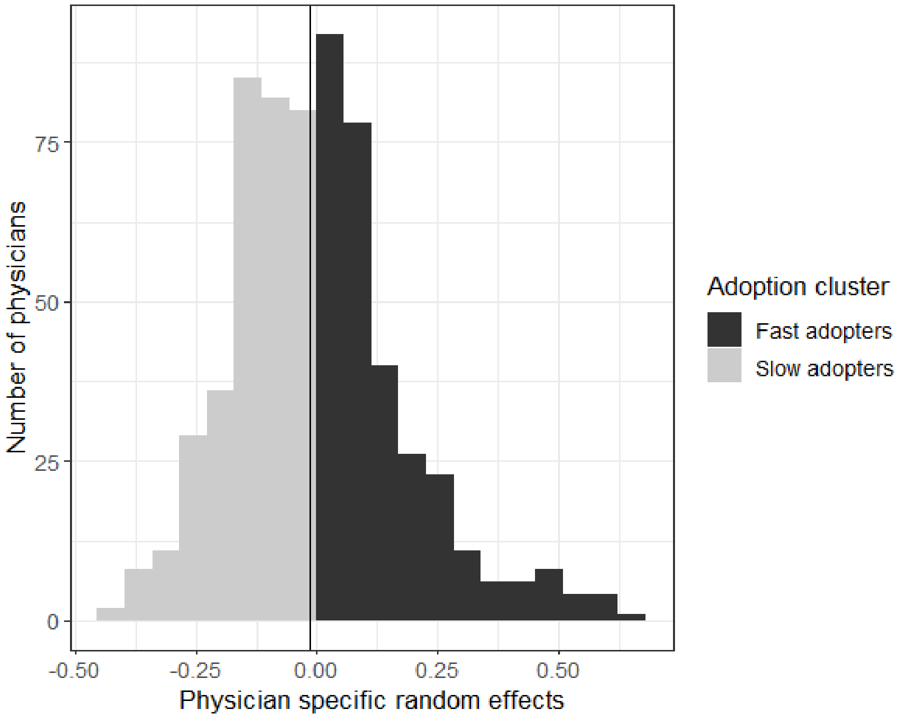
Tables and Figures

Figure 1.
Total volume of antibiotics for systemic use in OECD countries, 2017.



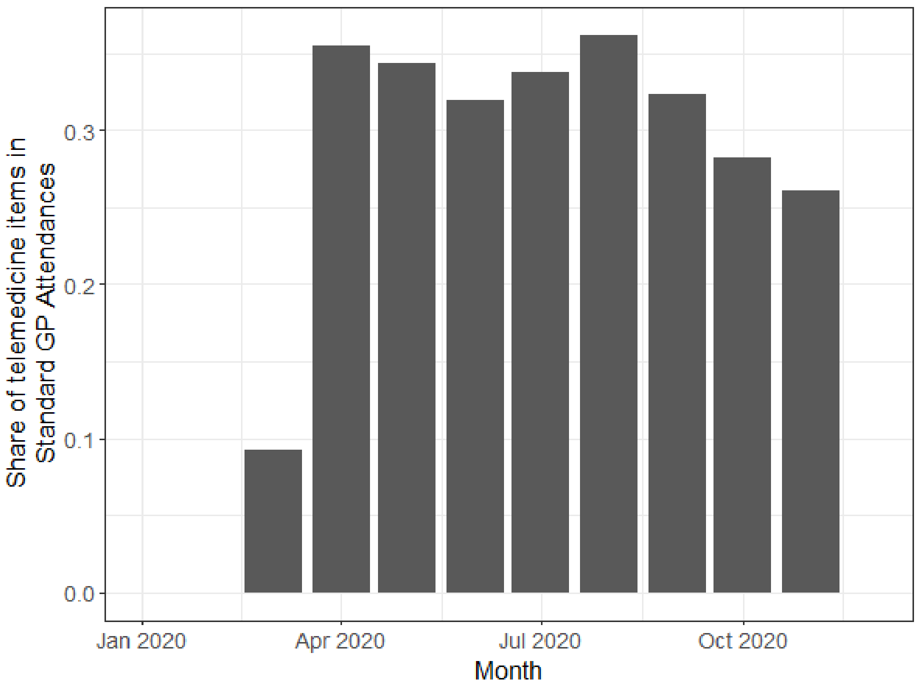
Note.— OECD healthcare quality and outcomes indicators sourced from https://www.oecd.org/health/health-care-quality-outcomes-indicators.htm [last accessed 22/5/24]. Defined Daily Dose (DDD) is the assumed average maintenance dose per day for a drug used for its main indication in adults. The year 2017 is chosen as it is the year for which most OECD countries provided data.

Figure 2.
Distribution of physician-specific random effects and telemedicine adoption group assignment.



Note.— Data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey and based on the physician sample defined in Section 4. Empirical distribution of physician random effects (u_{il}) from estimation of equation (1) in Section 3.1. Physicians with positive (negative) values of $\hat{u}_{il}$ are assigned to the fast (slow) adoption group.

Figure 3.
Share of telemedicine items of all Medicare-reported standard GP attendances in Australia, 2020.



Note.— Australian Medicare item reports data sourced from http://medicarestatistics.humanservices.gov.au/statistics/mbs_item.jsp [last accessed 22/5/24]. See Table A.2 for definitions of the Medicare items used in the chart.

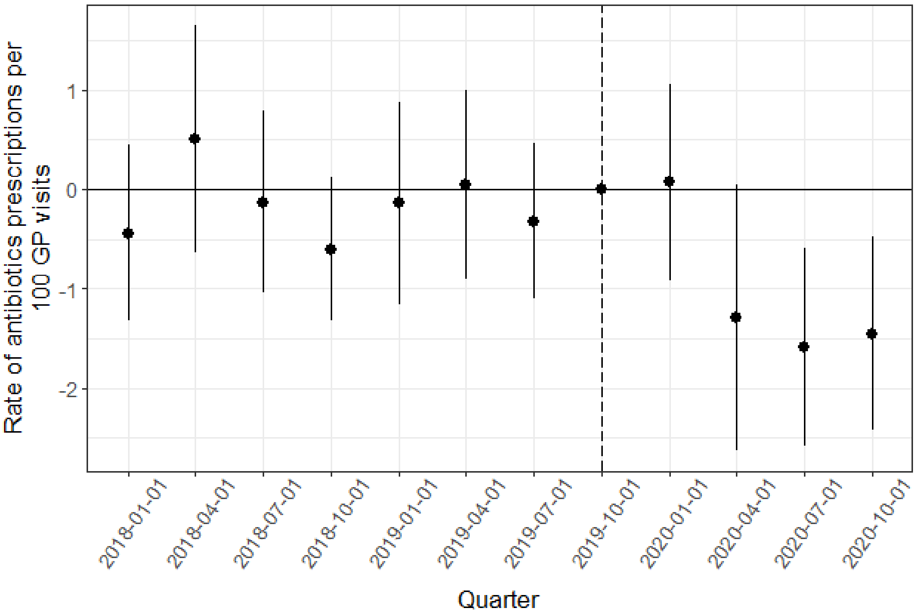
Table 1.

Sample summary statistics of physician characteristics by telemedicine adoption group.

	Mean		Physicians		Difference Fast-Slow	
	Fast adopters	Slow adopters	Fast adopters	Slow adopters	Coefficient	Standard error
Age	56.09	58.37	299	333	-2.279***	0.800
Female	0.532	0.429	299	333	0.102**	0.040
Graduated from medical school in Australia	0.795	0.717	298	332	0.078**	0.034
Part of the senior staff in a practice	0.431	0.416	288	322	0.014	0.040
Having majority of patients with complex health and social problems	0.768	0.678	289	323	0.090**	0.036
Number of patients seen in a typical week	89.71	91.99	284	317	-2.286	3.957
Number of nurses (practice size	3.346	3.244	286	322	0.102	0.177
Likely to engage in financial risks	0.097	0.073	290	330	0.024	0.023
Likely to engage in career and professional risks	0.090	0.058	290	330	0.032	0.021
Likely to engage in clinical risks	0.048	0.052	290	330	-0.003	0.018
Share of telemedicine in post-lockdown period	0.399	0.179	289	323	0.220***	0.012
Big 5 personality traits:						
Openness	0.002	-0.002	262	303	0.003	0.084
Conscientiousness	0.033	-0.028	262	303	0.061	0.085
Extroversion	0.060	-0.052	262	303	0.112	0.085
Agreeableness	-0.062	0.053	262	303	-0.115	0.084
Neuroticism	0.065	-0.056	262	303	0.122	0.085
Locus of control:						
Internal locus of control	0.030	-0.026	269	307	0.056	0.083
External locus of control	-0.017	0.015	269	307	-0.032	0.083
Tech-savvy:						
Agree that digital health technologies improve patient health outcomes and satisfaction	0.970	0.969	167	194	0.001	0.018
Agree that colleagues and support staff already extensively use digital health technologies	0.873	0.862	165	188	0.011	0.036
Agree that their patients are concerned about data privacy and security	0.800	0.770	160	183	0.030	0.044

Note.— Data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey and based on the physician sample defined in Section 4. Fast (slow) adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of equation (1) in Section 3.1. Big 5 personality traits and locus of control factors are standardised with mean zero and a standard deviation of one. The last column reports two-sample t-tests of differences in group averages between fast and slow adopters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 4.
Event study estimates on relative antibiotic prescribing rates by telemedicine adoption group.



NOTE.— Data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey and based on the physician sample defined in Section 4. Circles and associated vertical lines refer to coefficient estimates and 95% confidence intervals of τ_t (period-specific differences in outcome between fast and slow adopters of telemedicine) from estimation of equation (4) in Section 3.2, respectively. Fast (slow) adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of equation (1) in Section 3.1. The dashed vertical line indicates the baseline quarter used in the empirical model.

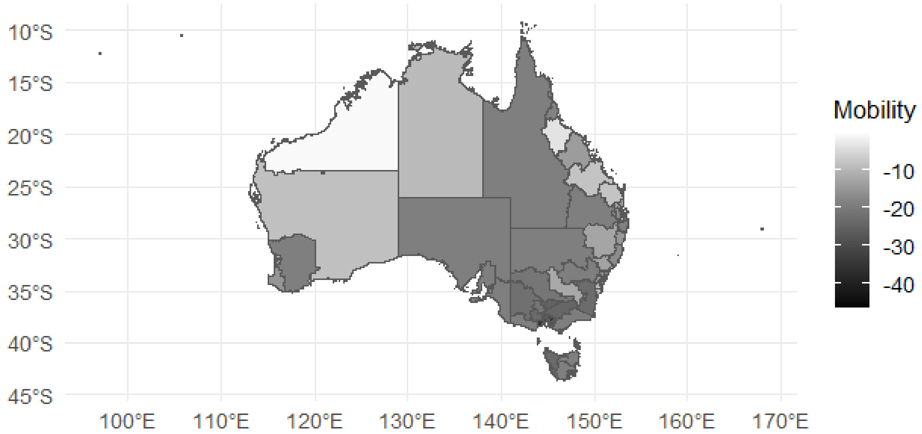
Table 2.

Difference-in-differences estimates of the association between antibiotic prescription outcomes and telemedicine adoption group.

	All states and territories		
	Mean	$\hat{\tau}$	Δ
Panel A			
Antibiotic prescription rate	14.65	-1.515*** (0.486)	-10%
Number of antibiotic scripts	103.7	-4.221 (3.380)	-4%
Number of attendances	706.9	42.19** (18.54)	6%
Panel B			
Antibiotic prescription rate	0.557	-0.050** (0.018)	-9%
Number of antibiotic scripts	103.7	-4.221 (3.380)	-4%
Total attendance duration	182.3	8.008* (4.268)	4%
Panel C			
Total fee revenue	39,949	652.8 (912.6)	2%
Total benefit paid	32,435	1,236 (755.5)	4%
Panel D			
Share acute antibiotics	0.376	-0.012 (0.007)	-3%
Share RTI-BS antibiotics	0.649	-0.030* (0.016)	-5%
Panel E			
Chronic condition script share	0.713	-0.003 (0.006)	0%
Total chronic condition scripts	736.4	-24.54 (18.89)	-3%

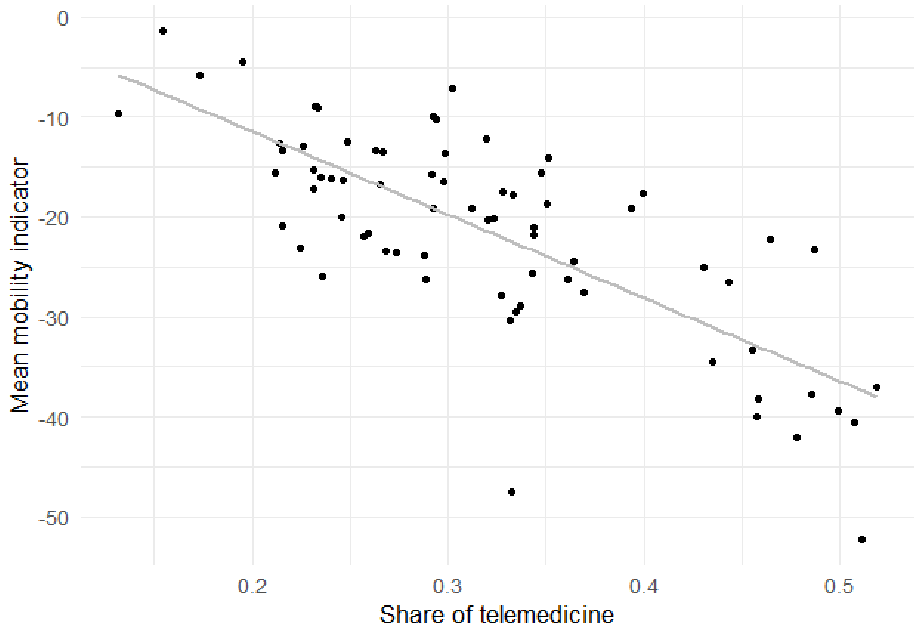
Note.— Data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey and based on the physician sample defined in Section 4. Reported coefficients and (standard errors) refer to estimates of τ (difference in outcome between fast and slow adopters of telemedicine) from estimation of equation (3) in Section 3.2, respectively. Fast (slow) adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of equation (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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE 5.
Google-reported mobility changes in Australia in 2020 by statistical area.



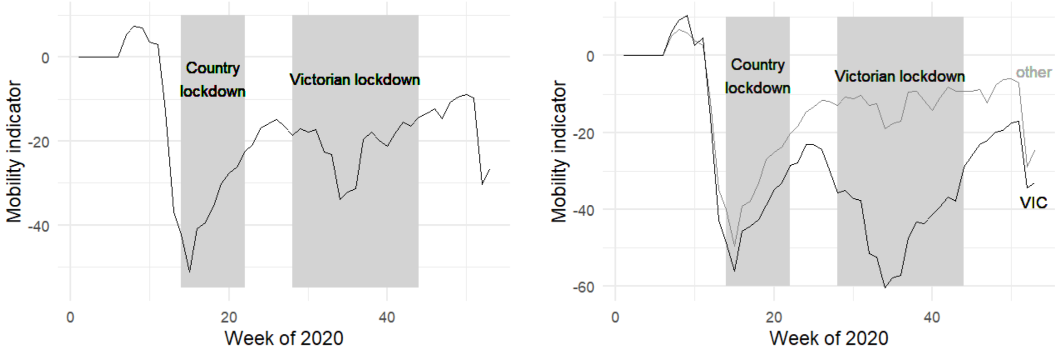
NOTE.— Data from Google LLC COVID-19 Community Mobility Reports sourced from https://www.google.com/covid19/mobility. The data extract consist of reported changes in mobility in Local Government Areas (LGAs), converted to statistical area (SA4) codes using a crosswalk from the Australian Bureau of Statistics (ABS), on a daily level compared to the median value, for the corresponding day of the week, during the first five weeks of 2020 pooled across three separate mobility categories: retail and recreation, transit, and workplace. Chart based on average mobility change between April and December, 2020. See also Section 6 for additional detail.

FIGURE 6.
Association between telemedicine shares and Google-reported mobility changes by statistical area.



NOTE.— Mobility data obtained from Google LLC COVID-19 Community Mobility Reports sourced from https://www.google.com/covid19/mobility. The data extract consist of reported changes in mobility in Local Government Areas (LGAs), converted to statistical area (SA4) codes using a crosswalk from the Australian Bureau of Statistics (ABS), on a daily level compared to the median value, for the corresponding day of the week, during the first five weeks of 2020 pooled across three separate mobility categories: retail and recreation, transit, and workplace. Chart based on average mobility change between April and December, 2020. Telemedicine data obtained from administrative records of all standard GP attendances conducted in 2020 provided by the Australian Bureau of Statistics (ABS). Markers and line correspond to quarterly area averages between April and December, 2020 and a fitted linear regression slope, respectively. See also Section 6 for additional detail.

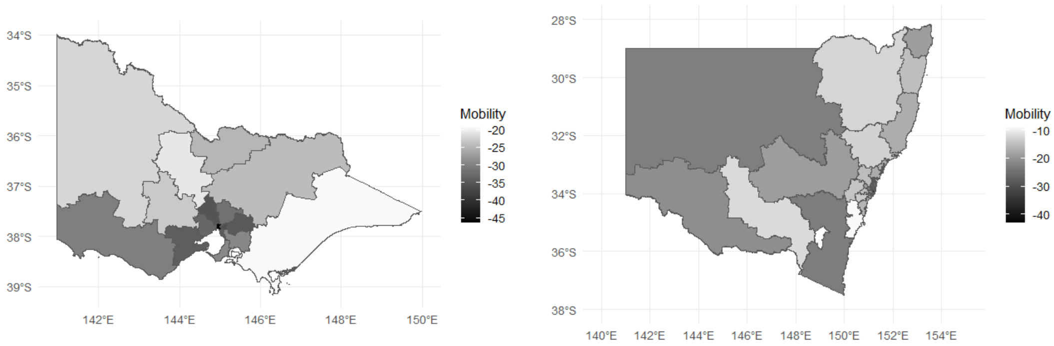
Figure 7.
Google-reported weekly mobility changes in Australia in 2020 by region.



(a) Australia (b) Victoria

Note.— Data from Google LLC COVID-19 Community Mobility Reports sourced from https://www.google.com/covid19/mobility. The data extract consist of reported changes in mobility in Local Government Areas (LGAs), converted to statistical area (SA4) codes using a crosswalk from the Australian Bureau of Statistics (ABS), on a daily level compared to the median value, for the corresponding day of the week, during the first five weeks of 2020 pooled across three separate mobility categories: retail and recreation, transit, and workplace. Chart based on average weekly mobility change throughout 2020. 'Other' in panel (b) refers to all states and territories except for Victoria. See also Section 6 for additional detail.

Figure 8.
Google-reported mobility changes in Victoria and New South Wales in 2020 by statistical area.



(a) Victoria (b) New South Wales

Note.— Data from Google LLC COVID-19 Community Mobility Reports sourced from https://www.google.com/covid19/mobility. The data extract consist of reported changes in mobility in Local Government Areas (LGAs), converted to statistical area (SA4) codes using a crosswalk from the Australian Bureau of Statistics (ABS), on a daily level compared to the median value, for the corresponding day of the week, during the first five weeks of 2020 pooled across three separate mobility categories: retail and recreation, transit, and workplace. Chart based on average mobility change between April and December, 2020. See also Section 6 for additional detail.

Table 3.
Difference-in-differences estimates of the association between telemedicine shares, mobility changes and regulatory strictness.

	(1) Apr-Oct	(2) Apr-Dec	(3) Apr-May	(4) Jul-Oct	(5) Nov-Dec
Victoria	0.174***	0.159***	0.115***	0.217***	0.169***
	(0.019)	(0.018)	(0.026)	(0.024)	(0.019)
Low mobility	0.010	0.016	-0.001	0.014	-0.004
	(0.011)	(0.011)	(0.016)	(0.014)	(0.011)
Victoria x low mobility	-0.028	-0.025	-0.053*	-0.011	-0.006
	(0.023)	(0.022)	(0.031)	(0.029)	(0.023)
Constant	0.302***	0.285***	0.337***	0.284***	0.307***
	(0.006)	(0.006)	(0.008)	(0.007)	(0.006)
Observations	301	387	84	168	82

Note.— Mobility data obtained from Google LLC COVID-19 Community Mobility Reports sourced from https://www.google.com/covid19/mobility. The data extract consist of reported changes in mobility in Local Government Areas (LGAs), converted to statistical area (SA4) codes using a crosswalk from the Australian Bureau of Statistics (ABS), on a daily level compared to the median value, for the corresponding day of the week, during the first five weeks of 2020 pooled across three separate mobility categories: retail and recreation, transit, and workplace. Telemedicine data obtained from administrative records of all standard GP attendances conducted in 2020 provided by the Australian Bureau of Statistics (ABS). Reported coefficients and (standard errors) refer to estimates of γ_0-γ_3 from estimation of equation (5) in Section 6.2 for different time intervals as indicated in column titles, respectively. See also Section 6 for additional detail. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

TABLE 4.
Difference-in-differences estimates of the association between antibiotic prescription outcomes and telemedicine adoption group by region.

	Victoria			Other			Victoria-Other		
Outcome	Mean	$\hat{\tau}$	Δ	Mean	$\hat{\tau}$	Δ	Mean	$\hat{\tau}$	Δ
Panel A									
Antibiotic prescription rate	14.33	-1.013	-7%	14.78	-1.387**	-9%	14.65	0.373	3%
		(1.050)			(0.575)			(1.174)	
Number of antibiotic scripts	100.3	2.561	3%	105.1	-4.898	-5%	103.7	7.459	7%
		(8.148)			(3.811)			(8.808)	
Number of attendances	705.4	47.54*	7%	707.5	32.10	5%	706.9	15.44	2%
		(24.90)			(23.96)			(34.09)	
Panel B									
Antibiotic prescription rate	0.553	-0.037	-7%	0.566	-0.044**	-8%	0.562	0.007	1%
		(0.044)			(0.020)			(0.047)	
Number of antibiotic scripts	100.3	2.561	3%	105.1	-4.898	-5%	103.7	7.459	7%
		(8.148)			(3.811)			(8.808)	
Total attendance duration	181.6	9.252	5%	183.1	4.998	3%	182.7	4.254	2%
		(5.846)			(5.543)			(7.946)	
Panel C									
Total fee revenue	40,225	1,134	3%	39,837	165.2	0%	39,949	968.7	2%
		(1,297)			(1,178)			(1,727)	
Total benefit paid	32,434	1,556	5%	32,436	714.5	2%	32,435	841.7	3%
		(1,031)			(982.2)			(1,405)	
Panel D									
Share acute antibiotics	0.368	0.006	2%	0.378	-0.011	-3%	0.376	0.016	4%
		(0.014)			(0.009)			(0.017)	
Share RTI-BS antibiotics	0.669	-0.057**	-9%	0.641	-0.003	0%	0.649	-0.053*	-8%
		(0.022)			(0.019)			(0.029)	
Panel E									
Chronic condition script share	0.721	-0.021	-3%	0.710	0.005	1%	0.713	-0.026*	-4%
		(0.014)			(0.004)			(0.014)	
Total chronic condition scripts	740.9	-6.234	-1%	734.6	-30.88	-4%	736.4	24.65	3%
		(27.31)			(24.85)			(36.40)	

NOTE.— Data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey and based on the physician sample defined in Section 4. Reported coefficients and (standard errors) in the first two sets of columns ('Victoria' and 'Other') refer to estimates of τ (difference in outcome between fast and slow adopters of telemedicine) from estimation of equation (3) in Section 3.2, respectively. Corresponding estimates in the last set of columns ('Victoria-Other') refers to estimates from estimating a fully interacted triple-difference model by including a Victoria dummy indicator as the third factor. Fast (slow) adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of equation (1) in Section 3.1. Means are based on outcome averages in 2019 across all sampled physicians in the regional group and Δ refers to the difference between the outcome-specific coefficient estimate $\hat{\tau}$ and the reported mean. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Does telemedicine affect prescribing quality in primary care?

— Online Appendix —

June 17, 2024

Table A.1.
Description of standard GP attendance items in Medicare Australia.

Medicare item	Fee (Benefit)	Medicare description
3: Level A GP Attendance	A$18.95 (100%)	Professional attendance at consulting rooms (other than a service to which another item applies) by a general practitioner for an obvious problem characterised by the straightforward nature of the task that requires a short patient history and, if required, limited examination and management-each attendance.
23: Level B GP Attendance	A$41.40 (100%)	Professional attendance by a general practitioner at consulting rooms (other than a service to which another item in this Schedule applies), lasting at least 6 minutes and less than 20 minutes and including any of the following that are clinically relevant: (a) taking a patient history; (b) performing a clinical examination; (c) arranging any necessary investigation; (d) implementing a management plan; (e) providing appropriate preventive health care; for one or more health-related issues, with appropriate documentation.
36: Level C GP Attendance	A$80.10 (100%)	Professional attendance by a general practitioner at consulting rooms (other than a service to which another item in the table applies), lasting at least 20 minutes and including any of the following that are clinically relevant: (a) taking a detailed patient history; (b) performing a clinical examination; (c) arranging any necessary investigation; (d) implementing a management plan; (e) providing appropriate preventive health care; for one or more health-related issues, with appropriate documentation-each attendance.
44: Level D GP Attendance	A$118.00 (100%)	Professional attendance by a general practitioner at consulting rooms (other than a service to which another item in the table applies), lasting at least 40 minutes and including any of the following that are clinically relevant: (a) taking an extensive patient history; (b) performing a clinical examination; (c) arranging any necessary investigation; (d) implementing a management plan; (e) providing appropriate preventive health care; for one or more health-related issues, with appropriate documentation-each attendance.

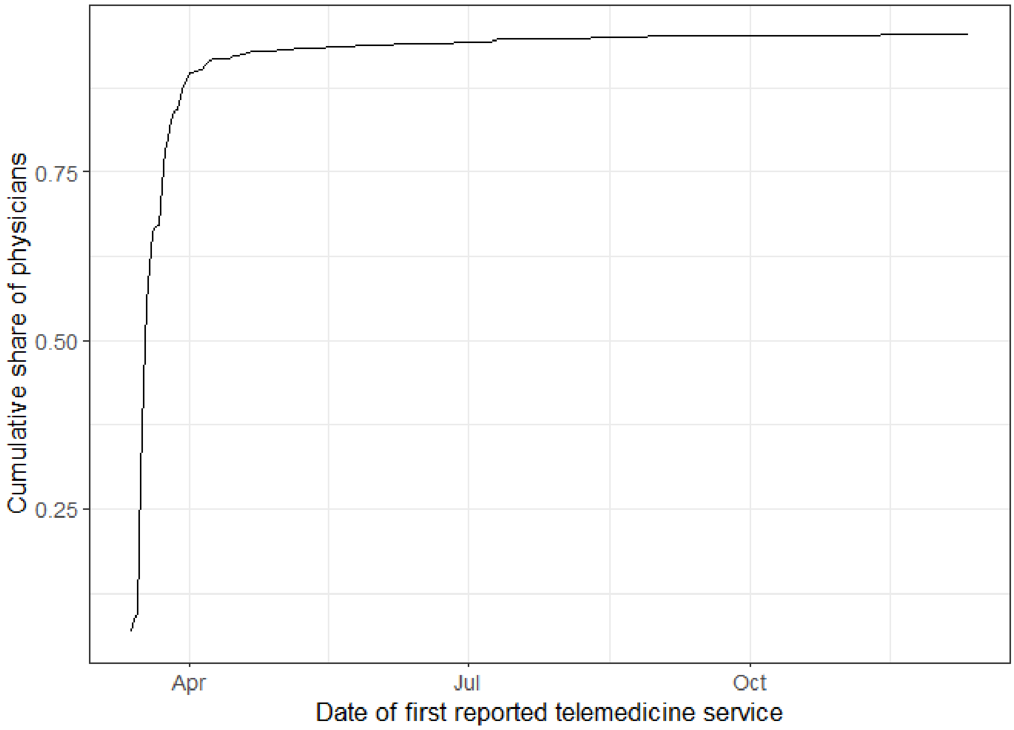
Note.— Australian Medicare item descriptions sourced from MBS Online: https://www.mbsonline.gov.au/ [last accessed 22/5/24]. MBS Online contains a listing of the Medicare services subsidised by the Australian Government by item number. Fee and benefit refers to the standard fee chargeable for the specific service and the Medicare subsidy associated with the service, respectively.

Table A.2.
Crosswalk between face-to-face and telemedicine standard GP attendance items introduced in Medicare Australia on 13 March, 2020.

Service	Existing items (face-to-face)	COVID-19 Telemedicine items (video)	COVID-19 Telemedicine items (phone)
Level A GP Attendance	3	91790	91795
Level B GP Attendance	23	91800	91809
Level C GP Attendance	36	91801	91810
Level D GP Attendance	44	91802	91811

Note.— COVID-19 Temporary MBS Telehealth Services sourced from MBS Online: https://www.mbsonline.gov.au/internet/mbsonline/publishing.nsf/Content/Factsheet-TempBB [last accessed 22/5/24].

FIGURE A.1.
Cumulative share of the first-time use of telemedicine Medicare items by date among physicians in the analysis sample.



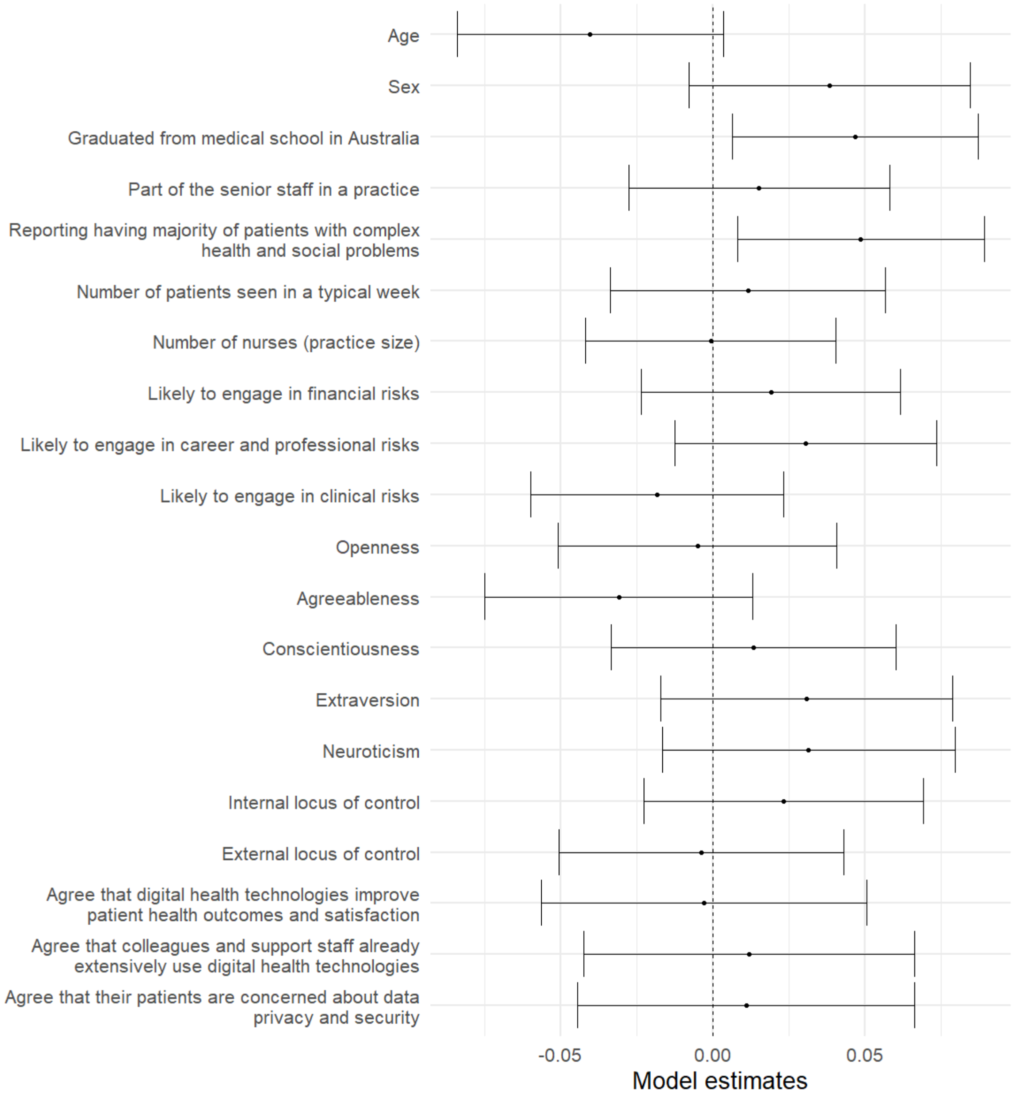
NOTE.— Data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey and based on the physician sample defined in Section 4. First-time use is defined as the first date when a physician is observed to have used a Medicare-subsidised telemedicine item for a standard GP attendance service (defined in Table A.2) as registered in the Medicare Benefit Schedule (MBS). Telemedicine item for standard GP attendances were first introduced on 13 March, 2020.

TABLE A.3.
Antibiotic drug categories and corresponding Anatomical Therapeutic Classification (ATC).

Category	ATC codes
All antibiotics	J01
Antibiotics predominantly prescribed for respiratory tract infections (RTI):	
Broad spectrum	J01AA02 J01CA04 J01CR02 J01FA06 J01FA09
Narrow spectrum	J01CE02 J01DB01

NOTE.— Antibiotic drugs and ATC codes sourced from the Australian Pharmaceutical Benefits Scheme (PBS): https://www.pbs.gov.au/ [last accessed 22/5/24]. Definition of antibiotics prescribed predominantly for Respiratory Tract Infections (RTI) and into broad and narrow spectrum RTI-related antibiotics are based on the classifications in Gillies et al. (2022) and Coenen et al. (2007), respectively.

FIGURE A.2.
Associations between telemedicine adoption group and physician-specific characteristics.



NOTE.— Data from the Medicine in Australia: Balancing Employment and Life (MABEL) survey and based on the physician sample defined in Section 4. Circles and associated horizontal lines and brackets refer to coefficient estimates and 95% confidence intervals from estimation of a multivariate regression model of a binary indicator for being a fast adopter of telemedicine on the full set of physician characteristics from Table 1 using a cross-section of the sampled physicians from the last MABEL wave in 2018. Fast (slow) adopters of telemedicine are defined by having a positive (negative) value of $\hat{u}_{il}$ from estimation of equation (1) in Section 3.1.