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The responses of physicians to a fall in demand for voluntary private health insurance.

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Abstract
This paper examines the impact of a fall in demand for voluntary private health insurance on physician behaviour. We find that dual practice physicians who earned more revenue from working in private hospitals before the fall in demand for PHI were more likely to experience a fall in the volume of private hospital care and a less complex mix of in-hospital services provided. Risk-averse doctors drove this reduction in complexity. There was weak evidence suggesting that doctors compensated for the fall in volume by increasing their working hours in public hospitals and reducing fees for in-hospital services. We found no evidence of higher volumes of care in out-of-hospital visits to compensate for the lower in-hospital volumes, but some weak evidence of claiming for more complex and costly out-of-hospital services, which we interpret as upcoding. Compensatory behaviours were small and primarily observed among risk-averse male doctors with low conscientiousness, from non-surgical specialties, and located in areas with lower doctor density.

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Introduction

This paper focuses on the role of the demand for health insurance in influencing physicians' behaviour. Expansions of health insurance can, compared to no insurance, increase utilization and health outcomes (Aron-Dine, Einav, & Finkelstein, 2013; Baicker et al., 2013; Card, Dobkin, & Maestas, 2008; Erlangga, Suhrcke, Ali, & Bloor, 2019; Finkelstein et al., 2012; Newhouse, 1993). Central to securing improvements in utilization and health outcomes is the availability of physicians and other healthcare providers. Increased demand initiated by newly insured patients or from increased coverage for those who already have health insurance should stimulate physician supply in the short and long run (T. Buchmueller, Miller, & Vujicic, 2016; Card et al., 2008; Cometto, Boerma, Campbell, Dare, & Evans, 2013; Garthwaite, 2012; Huh, 2021; Sloan, 1982). The behavioural impacts of this increase in supply depend on the details of the health insurance coverage.

Literature on the effects of insurance expansions on physician behaviour have focused on short run changes and found associations with increased prescribing (Hu, Decker, & Chou, 2017), reduced consultation length, re-allocation of hours worked between different insurance schemes or between the private and public sectors (T. Buchmueller et al., 2016; Chen, Lo Sasso, & Richards, 2018; Cheng, Kalb, & Scott, 2018; Garthwaite, 2012; He & White, 2013; Maclean, Popovici, & Stern, 2018; Neprash, Zink, Sheridan, & Hempstead, 2021; Richards & Tello-Trillo, 2019), increased fees (Dormont & Péron, 2016; Maclean et al., 2018; Sloan, 1982; Triyana, 2016; Yu, van Gool, Hall, & Fiebig, 2019), increased sub-specialty choice (Chen et al., 2018), increased human capital investments (Clemens, Gottlieb, & Hicks, 2021), changes in the location of practice (Huh, 2021), and hiring more non-physician health care workers (T. Buchmueller et al., 2016; Dillender, 2022; Dinardi, 2021). In the long run, given the long lead times in physician training, more physicians would enter training due to the increased returns on their investment in human capital.

The above literature examines health insurance expansions for individuals initially without health insurance and originates from the United States. Several other countries have supplementary private insurance coverage in addition to universal healthcare insurance, including France, Belgium, Germany, Australia, Ireland, Italy, Portugal, Spain, and the UK. In these settings, those with supplementary PHI often have higher utilization of health care compared to those with only public coverage (T. C. Buchmueller, Couffinhal, Grignon, & Perronnin, 2004; Cameron, Trivedi, Milne, & Piggot, 1988; Cheng, 2014; Doiron & Kettlewell, 2018; Eldridge, Onur, & Velamuri, 2017; Franc, Perronnin, & Pierre, 2016; Jones, Koolman, & Doorslaer, 2006; Sevilla-Dedieu, Billaudeau, & Paraponaris, 2020; Stabile, 2001; Vera-Hernández, 1999). However, there is no evidence on physicians' responses to changes in coverage of supplementary PHI. Supplementary private health insurance is voluntary, with medical services provided by physicians working in the private sector or undertaking dual practice.

This paper examines a situation in which the demand for voluntary private health insurance declines. We focus on the short-run responses of physicians to a fall in the percentage of the population covered by supplementary private health insurance. In Australia, universal public health insurance, Medicare, enables free access to public hospitals and provides subsidies for services provided by private medical practitioners (GPs and other specialists) outside of hospitals, as well as subsidies for private hospital inpatient services and pharmaceuticals. In March 2022, 45.1 percent of the Australian adult population held supplementary private health insurance covering private hospital services. Private health insurance (PHI) has benefits over Medicare public hospital coverage that include significantly reduced waiting times for medical care, choice of senior physician for private hospital care, higher level of amenity and resources (e.g. private room) and also provides 'peace of mind' for risk-averse individuals (Zhang & Prakash, 2021). Individuals may also be better off financially by taking out PHI because the federal government subsidizes premiums and coverage. Additionally, there are tax penalties for those above certain income thresholds who do not have PHI, such that for some, the cost of the PHI premium is less than the tax penalty.

For those who choose to use their PHI instead of Medicare, there are uncertain out-of-pocket costs for medical services. Medical practitioners in private practice are paid by fee-for-service and are free to charge any fee they wish, allowing them to engage in price discrimination. The subsidies patients receive from Medicare and from PHI for medical services provided by physicians are often viewed by physicians as insufficient, and so patients using private medical practitioners can face an out-of-pocket cost. Using PHI can lead to uncertain additional out-of-pocket expenses that may influence decisions to both purchase PHI and subsequently use it.

This paper aims to examine whether a decline in demand for supplementary private health insurance coverage caused a reduction in demand for private medical care and changed physician behaviour. The proportion of the population with hospital PHI cover dropped from a peak of 47.4 percent in June 2015 to 43.8 percent by March 2020. The growth in the number of those with PHI was 1 percent per year on average from June 2013 until it began to slow down in June 2015. By March 2016, it had flattened out, and it started to decline in every quarter after March 2017.

This fall has been attributed to several factors that have reduced the value of supplementary PHI, including rising PHI premiums, increasing rates of policy exclusions, higher policy excesses, and rising out-of-pocket costs for medical care that people incur when using PHI. Combined with relatively low wage growth, PHI and private medical care were becoming less affordable with profit warnings for private insurers and private hospital groups in 2016. We consider the start of the fall in PHI membership in March 2015 as the point at which the effects of these trends began to reduce the growth in coverage and impact private hospitals.

We use a continuous difference-in-differences model to examine the impact of the fall in demand for private health insurance on private hospital utilisation and physician behaviours. We use rich and representative physician survey data linked to administrative billing data. Dual practice physicians earning 1 per cent more revenue from private hospitals before the fall in demand for PHI experienced 9.7 per cent fewer claims per quarter for private in-hospital care after the fall in demand for PHI, and a less complex mix of in-hospital services provided. Our heterogeneity analysis suggested that risk-averse doctors drove this reduction in complexity. In terms of behaviour to offset this fall in utilisation, there was weak evidence suggesting that doctors increased their working hours in public hospitals by 1.7 per cent and reduced fees for private in-hospital services. We found no evidence of higher volumes of care in private out-of-hospital visits to compensate for the lower private in-hospital volumes. There was weak evidence of doctors claiming for more complex and costly out-of-hospital services, which we interpret as upcoding. These behaviours were primarily observed among risk-averse male doctors with low conscientiousness, from non-surgical specialties, and located in areas with lower doctor density.

Our research makes several contributions to the literature. We contribute to the literature on the effects of health insurance on healthcare utilization and expenditures by examining the impact of a reduction in demand for supplementary PHI. We also contribute to the knowledge about physician responses to incentives resulting from a decline in demand for their services and how they compensate for the resulting revenue loss. Physicians' responses to financial incentives are an important area of research, as their responses can influence healthcare costs, access, and the quality of care provided. In our context, a fall in demand for PHI and private healthcare affects physician behaviour because it can reduce revenue, especially with volume-based fee-for-service payment. In addition to examining the effects on utilization, we also investigate the impact on fees charged, the mix of services between private in-hospital procedures and out-of-hospital consultations, upcoding, and hours worked in private hospitals, as physicians can also adjust their labour supply (Cheng et al., 2018).

Much previous research on insurance and the utilization of private hospitals, especially in Australia, has employed population surveys and relies on self-reported measures of healthcare utilization. These measures have been shown to produce measurement error depending on the recall period in the survey question (Dalziel, Li, Scott, & Clarke, 2018). We examine the effects using physician-level administrative data and contribute to the literature by linking rich survey data to administrative claims data, allowing us to explore the heterogeneity of physician responses to the fall in demand according to key characteristics, including speciality, gender, personality traits, and risk aversion.

Institutional setting.

Health expenditure in Australia is 10.2 percent of GDP (AIHW, 2021). Australia's healthcare system is a mix of public and private provision and financing. Medicare is funded by taxation and provides free access to public hospitals. Patients also receive subsidies from Medicare for services provided by private medical practitioners, including GPs and other specialists. Pharmaceuticals are also heavily subsidized. In addition to Medicare, individuals can opt to purchase PHI that essentially duplicates Medicare coverage. Policies provide coverage for treatment as a private patient in public and private hospitals, as well as policies for ‘extras’ cover, including allied health, dental, and optical services. PHI cannot cover the costs of services provided outside of hospitals by GPs and other private specialists (e.g. in their offices and practices).

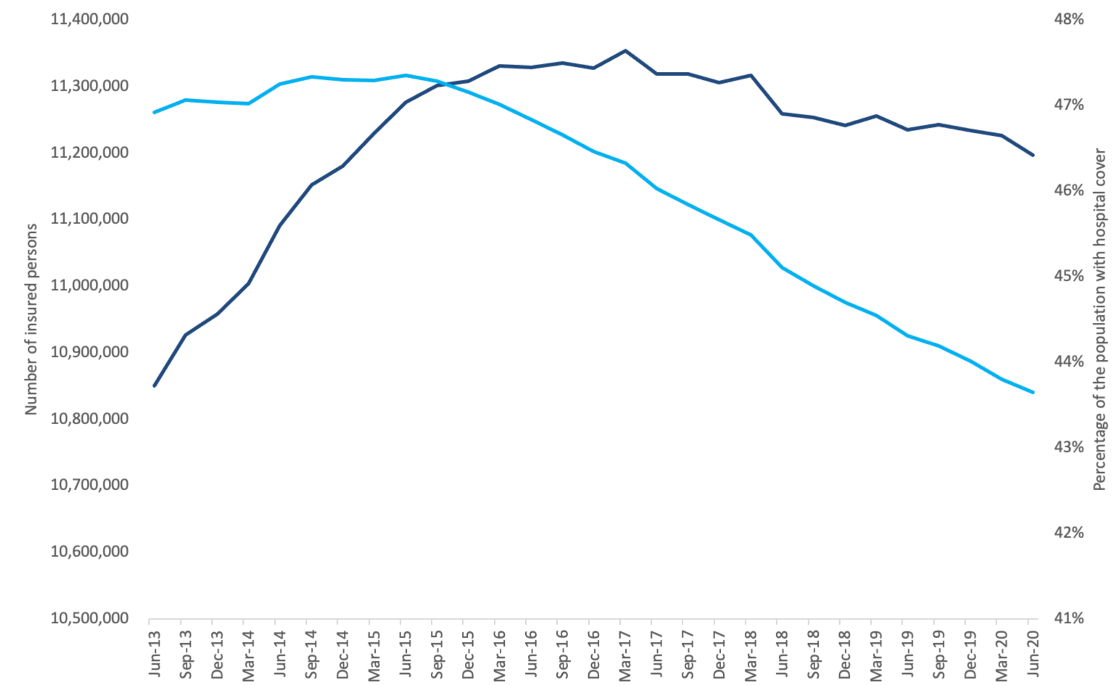
The Australian government subsidizes the purchase of private health insurance through general taxation, who since 1999 provided subsidies for premiums that depend on age and income, and also introduced the Medicare Levy Surcharge (MLS), a tax incentive, where between 1 percent and 1.5 percent of additional tax is paid for people who do not have PHI, and this also depends on income, with higher tax penalties for those on higher incomes.

In 2017/18, around 47 percent of all hospitals in Australia were private, with 657 private hospitals, including 357 private freestanding day hospitals (AIHW, 2019). In 2016-17 62 percent of private hospitals were ‘for profit’ (ABS, 2018). The private hospital sector had around one-third (34,300 beds in 2016-17) of total hospital beds in Australia, comprised 40 percent (4.5 million separations in 2017-18) of total hospital separations, undertook 66 percent (1.49 million admissions) of all elective surgery, 33 percent (9.98 million patient days) of total patient days (AIHW, 2019), and had a total income of $14.3 billion (ABS, 2018). The revenue of private hospitals comes from a range of sources, with almost 80 percent from private health insurers, which include government subsidies, 13 percent from federal and state governments, 3.8 percent directly from patients, and 2.3 percent from other sources (ABS, 2018). Eighty per cent of non-GP specialists engage in dual practice, working in both public and private hospitals, as well as private offices.

Medical practitioners working outside of public hospitals (GPs and other specialists) are paid by fee-for-service. They have the freedom to charge any fee and can engage in price discrimination. A patient who has treatment in a private hospital will have their hospital stay funded by their PHI, often with an excess depending on their policy. Medical practitioners are typically not employed by private hospitals, but rather have an arrangement that allows them to admit patients and use the hospital's facilities. Separate from hospital charges covered by PHI, medical practitioners charge patients a fee for the services they provide in hospital. Medicare subsidizes a proportion of a doctor's fee according to a list of fees set out in the Medicare Benefits Schedule. For services provided in-hospital, the subsidy (benefit) the patient receives is set at 75 percent of the MBS fee. PHI is required to cover the remaining 25 percent. For doctors who charge above 100 percent of the MBS fee, this can be covered by PHI, and/or patients can pay an out-of-pocket amount. PHI can cover either the whole gap between the MBS fee and the doctor's fee (gap cover) or a proportion of the gap (known as gap cover). For patients, gap cover is only offered if the doctor has an agreement with a specific insurer. If not, then the patient pays the full gap. If doctors do have a gap cover agreement with an insurer, they can choose not to use it for a specific patient, with the patient paying the full gap, which is another form of price discrimination. Suppose a doctor decides to use gap cover. In that case, each health insurer has a list of fees, and the doctor agrees to charge that fee for each service provided, with the patient facing no out-of-pocket cost (gap cover) or a reduced out-of-pocket cost (known as gap cover). For approximately 50 percent of medical services in private hospitals, there are no out-of-pocket costs, as gap cover is utilized.

Following steady increases in PHI coverage after the 2001 increase in subsidies, the percentage of the population with PHI hospital coverage peaked at 47.4 percent in June 2015 and declined to 43.6 percent by March 2020 (Figure 1). The growth in the total number of insured persons also started to fall around June 2015, and after peaking in the first quarter of 2017 at 11,353,517, the number fell every quarter until March 2020 (by 1.2 percent to 11,223,363: a net fall of 130,154 insured persons). Most of those dropping coverage were under 60 years old, where the number of insured persons fell by 318,716; however, the number increased for those aged 60 years or older by 188,562.

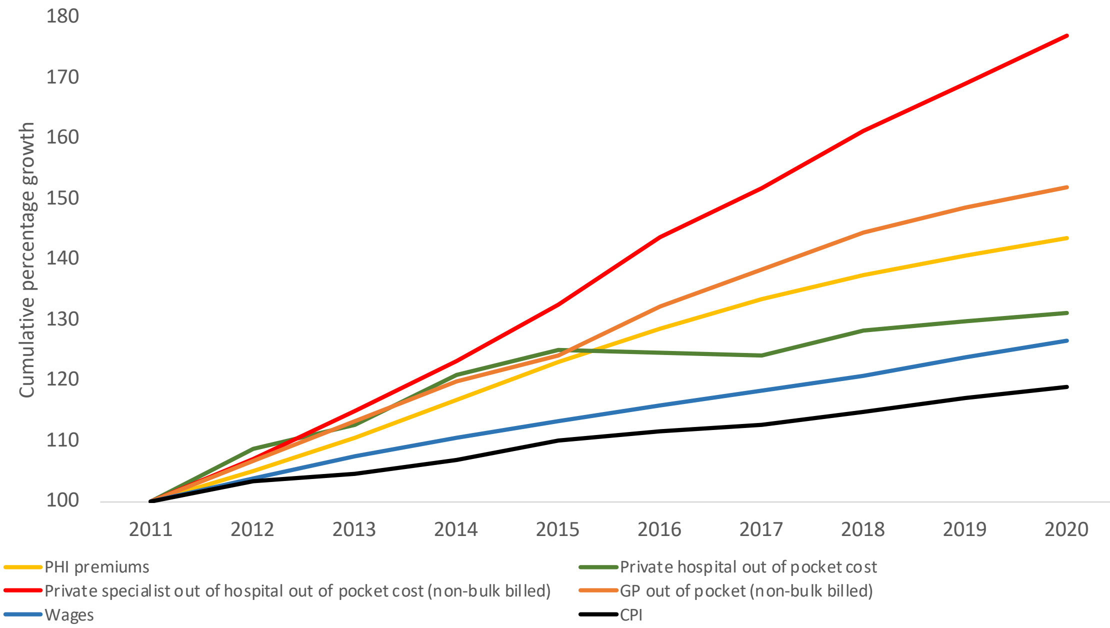
Figure 1. Supplementary private hospital health insurance coverage in Australia, June 2013 to June 2020.



Source: APRA (2022)

The reasons for the drop in PHI coverage were consumers' increasing concerns about the value of private health care. These concerns included growth in out-of-pocket costs, including private health insurance premiums and fees for medical services provided by GPs and non-GP specialists, as well as the decline in coverage of private health insurance policies. Since July 2012, healthcare costs have grown faster than wages (Figure 2), which have been increasing but at a much slower rate. These trends have produced a widening gap between growth in private health costs and household incomes over time, with a cumulative effect on affordability that is associated with the fall in PHI coverage and membership from June 2015. In 2018, there was widespread national publicity about increasing medical out-of-pocket costs.

Figure 2. Growth in health prices, wages and consumer price index, 2011 to 2020



Source: GP out of pocket costs and private specialist out of hospital out of pocket costs (Department of Health, 2021), PHI premiums (Departmrentof Health and Aged Care, 2022), Private hospital out of pocket costs (includes hospital and medical charges) (Department of Health and Aged Care, 2021), Wage price index (ABS, 2022b), Consumer Price Index (ABS, 2022a).

Additionally, there is some evidence that consumers were receiving less value for their PHI premiums, as indicated by reductions in the scope of coverage of PHI policies and an increase in consumer complaints (Senate Community Affairs References Committee, 2017). The proportion of insured persons with a policy that includes exclusions for particular medical conditions increased from 36 percent in December 2015 to 58.7 percent in December 2019, whilst the proportion of insured persons with a policy that has an excess or co-payment increased from 82.8 percent in December 2015 to 87 percent in December 2019 (APRA, 2020). In October 2016, announcements of profit warnings from Medibank Private, Australia's largest private health insurer, and Healthscope, a private hospital group, were published and were accompanied by a fall in share prices for the two largest for-profit private hospital operators (Ramsay and Healthscope), with Healthscope eventually being delisted from the stock exchange and sold. Mounting pressure from the private health sector and consumers about rising out-of-pocket costs led to a government review in 2017. These issues were documented extensively by the resulting Senate Committee report in 2017 (Senate Community Affairs References Committee, 2017), by the Australian Competition and Consumer Commission reports on private health insurance (Australian Competition and Consumer Commission, 2018), by the general media.

Data

Two sources of data are used and merged for the analysis. The Medicine in Australia: Balancing Employment and Life (MABEL) is a panel survey of Australian doctors that collected annual data over 11 years, from 2008 to 2018 (Joyce et al., 2010; Szawlowski, Harrap, Leahy, & Scott, 2020). Doctors were mailed an invitation letter that contained a hard copy of the survey and login details, allowing them to choose whether to complete it online if they preferred (Taylor & Scott, 2019). They were sent three mailed reminders. The survey contains rich information on doctors' personal attributes and work characteristics. Four different types of surveys were administered: to GPs, non-GP specialists, doctors enrolled in specialty training programs, and doctors newly qualified who have not yet chosen their specialty training program.

In 2015, we requested consent from around 12,000 qualified GPs and non-GP specialists who had previously completed a MABEL survey to link their survey responses to all of their MBS claims between 2011 and 2020: 2,216 consented to linkage. The MBS data are at the level of each MBS claim made[1]. For each claim, the data includes the MBS item number (e.g., item 23 for a GP consultation), the broader group it belongs to (e.g., A1: unreferred GP attendances), the date when the service was provided, the doctor's total fee they charged to the patient, MBS schedule fee, the MBS benefit paid to the patient, and a unique doctor identifier that is used to link the MBS data to the MABEL survey. The data include each consenting MABEL respondent's complete claims history across all the locations in which they practice. For those working in multiple locations, we use their 'main' geographic location at the time they responded to the MABEL survey since the MBS data did not include location information. We include doctors who did not change their primary location of work. The MBS data do not include any patient characteristics or a patient identifier for each claim. For each doctor, all claims were obtained from October 2011 to December 2020.

[1] Note these data do not include activity for public patients in public hospitals.

For the analysis, we aggregate the data to the doctor-quarter-year level, since doctor-level behaviour is of interest and the unit of analysis. Due to the difference in data frequency, annual information on each doctor from MABEL is duplicated to match the quarterly frequency of MBS claims data. We link waves 4-11 (2011 to 2018) of MABEL with quarterly MBS claims level data from the last quarter of 2011 to the second quarter of 2019 (the 2018 wave of the MABEL survey was in the field between August 2018 and April 2019). We remove doctors who, in the MABEL survey, indicate their specialty as pathologists, diagnostic radiology, medical administration, psychiatry, or public health. These groups primarily provide out-of-hospital services, whereas our focus is on in-hospital services. We include only doctors providing medical services to patients in private hospitals, as these are the ones directly affected by the fall in demand for PHI. We include data from non-GP specialists who provided at least one in-hospital service ($y_{ijt}^{h} > 0$) in every quarter-year pre-2015. We exclude doctors who changed their geographic location after 2015, as this may affect their activity and not be related to the fall in demand.

The estimation sample is 15,120 observations from 588 non-GP specialists. To enhance external validity, given the small sample size of doctors, we compare the characteristics of our sample to those of the 2015 population of doctors (when doctors consented and at baseline) and calculate inverse probability weights, which are used in all regression analyses (Table 1).

Dependent variables

The analysis is conducted at the doctor level and will examine the effect of the fall in demand for PHI on utilization for each doctor, fees charged, the mix of services between private hospital procedures and out-of-hospital consultations, hours worked in private and public hospitals, and upcoding. The (net) impact of the fall in demand for PHI on the utilization of private healthcare is uncertain, as it depends on whether people use healthcare and, if they do, whether they choose to use private or public hospitals for their treatment. The under-60s, who were more likely to drop cover, are likely to be healthier and have fewer chronic conditions on average than the over-60s who continued to buy PHI. The under-60s also include those eligible for national screening programs for cancer and also women using obstetrics and gynaecology services, for example.

Unfortunately, our data do not contain any information on patient age, gender, or health conditions, and so we examine the impact on physician-level utilization and behaviour.

If utilization falls, physicians can respond in several ways. Since private health insurance does not cover services provided by private specialists outside of hospitals, these services (largely consultations in physicians' offices) will not be directly affected by the fall in PHI. However, there may be indirect effects or spillovers as these visits are part of an overall treatment pathway. Since doctors optimize across all of the care they provide, they could schedule more follow-up out-of-hospital visits or accept more new patients to maintain their earnings when the number of hospital services falls. The decline in demand for private hospital care may also lead to a decrease in demand for private out-of-hospital consultations. For each doctor, our data includes the entire universe of MBS items claimed, allowing us to examine these spillovers.

For each doctor at each time point, we first define dependent variables related to services provided to private patients in hospital, y^h, which are funded by PHI policies (as well as Medicare and out of pocket payments) and are so directly affected by the fall in demand for PHI, and services provided out of hospital, y^o, which are not funded by PHI policies but are funded by Medicare and out of pocket payments, and so are indirectly affected by the fall in demand for PHI.

In the MBS data, all services provided as part of an episode of private hospital treatment attract a 75 percent subsidy of the MBS fee. If the patient has PHI, their policy covers the 25 percent difference up to 100 percent of the MBS fee. We therefore define private hospital services as all services that attract a 75 percent MBS benefit (where the MBS benefit paid divided by the MBS fee equals 0.74 to 0.76 to account for rounding). All other services are classified as out-of-hospital services and attract 85 percent or more of the scheduled fee as benefits, and can include consultations, as well as diagnostic tests and some minor procedures performed in physicians' offices.

Dependent variables for in-hospital y^h and out-of-hospital services y^o include the total number of services claimed per doctor per quarter, which our utilization measures[2]. We also measure the

[2] Our data cannot link individual Medicare claims to patients so we cannot measure intensity of services per patient.

share of in-hospital to out-of-hospital services provided by each doctor, as doctors who experience a decline in demand for private hospital services may increase their provision of out-of-hospital consultations, for example, by recommending more follow-up visits. If patient-initiated utilization falls, physicians have incentives to increase physician-initiated utilization. The net effect is that we may not observe an increase in overall utilization depending on the size of this effect. However, our data can distinguish between some categories of patient-initiated utilization and physician-initiated utilization. For most specialist out-of-hospital consultations, separate MBS items are available for an initial consultation and a subsequent follow-up consultation for the same patient, with the latter attracting a lower MBS fee. The patient and their GP initiate initial consultations, whilst subsequent office visits are initiated by the physician who provided the initial consultation and asks the patient to return for a follow-up visit. For out-of-hospital services (not eligible for a 75 percent rebate), we also define the number of physician-initiated consultations per doctor per quarter using 25 MBS specialist attendance items identified as 'subsequent' visits.

A second response to a fall in demand is to adjust fees. Since the fall in demand is influenced by growing out-of-pocket costs relative to wages, increasing fees (and therefore out-of-pocket costs) is unlikely to be an option. A more usual market response when demand falls is to reduce prices. This response assumes that demand is elastic to some extent and that patients are aware of the decline in private specialist consultation fees. A decrease in fees would likely encourage patients to return. This response may also be more likely for doctors facing more competition where demand may be more elastic. We could also expect no effect on prices if patients cannot easily observe price information. Patients are referred by their GPs, given the gatekeeping system, and during our period of analysis there was no published information on specialists' fees or price transparency tools. The MBS data includes the provider charge (the full fee) for each item, and so we calculate the average fee per claim, for each doctor and quarter. For out-of-hospital consultations, we also calculate the proportion of claims that are bulk billed, where the MBS benefit for each item equals the provider charge.

A third possible response is to claim for a more profitable mix of services. The potential for upcoding is captured by the average Medicare schedule fee per claim, which is fixed for each item by Medicare (this is the Medicare subsidy). If the average schedule fee per claim rises for each doctor, it suggests that on average doctors are claiming for more expensive/complex services. This can be the result of upcoding, where doctors may choose to use more expensive items in their claims, for example, for longer consultations or more complex procedures than were provided. Another explanation is that the fall in demand was concentrated amongst patients with less severe conditions, leaving doctors with more complicated patients. We test for this by using a measure of patient complexity as a dependent variable from the MABEL survey data: specialists' self-reported level of agreement with the statement "*The majority of my patients have complex health and social problems*", with the following response categories: strongly agree/agree equal to 1 and zero otherwise.

Finally, we also examine whether doctors change their labour supply by analyzing their hours worked in private hospitals, public hospitals, and private consultation rooms (i.e., out-of-hospital settings). They may reduce their working hours in private hospitals and increase them in other settings. The MABEL survey asked respondents about their hours of work across different settings "*Excluding after-hours and on-call, for how many HOURS in your MOST RECENT USUAL WEEK at work did you undertake in each of the following settings?*" The response options included private hospitals, public hospitals and private consulting rooms.

Empirical analysis

We use a quasi-difference in differences model with a continuous treatment (Angrist & Pischke, 2008; Callaway, Goodman-Bacon, & Sant'Anna, 2024; Card, 1992) that has also been used in the health context to examine the effects of competition and hospital payment (Acemoglu & Finkelstein, 2008; Brekke, Canta, Siciliani, & Straume, 2021; Cooper, Gibbons, Jones, & McGuire, 2011; Gaynor, Moreno-Serra, & Propper, 2013; Longo, Siciliani, Moscelli, & Gravelle, 2019; Moscelli, Gravelle, & Siciliani, 2021). This is a 'dose-response' difference-in-difference model (Callaway et al., 2024). All doctors working in private practice were exposed to the fall in demand for PHI after mid-2015. What differs amongst these doctors is the extent of their exposure to the private sector before the fall in demand. Exposure is measured by the total fee revenue from private hospital work averaged over the years before 2015. This is defined as the total revenue from fees (including MBS subsidies, payments by PHI and patient out-of-pocket payments) for each doctor per quarter for in-hospital services. This represents each doctor's total gross earnings from working in private hospitals (before tax and before practice costs), as measured by the sum of the provider charge (total fee charged) per doctor per quarter.

We test whether those with higher pre-2015 total revenue were more likely to change their behaviour after 2015. We estimate the following two-way fixed-effects model:

$$y_{ijt} = \beta \bar{r}_{ij} \cdot post_t + \alpha_{ij} + \gamma_t + \theta_j + \epsilon_{ijt} \qquad (1)$$

Where y_{ijt} is one of the outcome variables for doctor i, in geographical area j at quarter t, $\bar{r}_{ij}$ is the exposure variable – the mean total revenue from working in private hospitals of doctor i in geographical area j in each year-quarter between 2011 and 2014, the years before the fall in demand for PHI. This is constant for all doctors throughout the pre and post-periods. The pre-post 2015 dummy variable is $post_t$.

β measures whether the effect of the drop in demand for PHI on outcomes after 2015 depends on the pre-2015 revenue from working in private hospitals. Since $\bar{r}_{ij}$ is not normally distributed (skewed to the left) the log of $\bar{r}_{ij}$ is used in the main regression models.

In addition to equation 1, we also use quartiles of revenue $\bar{r}_{ij}$ and use the bottom quartile as a 'control group' to compare those with low exposure to private hospital care with those who have higher exposure. This comparison tests the same hypothesis as in equation 1 and can be used to provide additional evidence on parallel trends.

Identification relies on the parallel trends assumption that the evolution of outcomes post-2015 is the same between doctors with marginally higher revenue compared to those with marginally lower revenue from private hospital work before 2015. More precisely, if those with higher revenue before 2015 were to reduce their revenue, then the evolution of outcomes would be the same as those who actually had lower revenue before 2015 (Callaway et al., 2024). This should be the case for comparisons of all marginal values of pre-2015 revenue. Given that this is a continuous variable, it requires that doctors with very slightly different levels of revenue have the same evolution of potential outcomes, regardless of their place in the revenue distribution. Our identification strategy relies on the assumption that physicians with higher private revenue do not systematically differ in ways that affect their responsiveness to demand shocks, such that treatment effects should be homogenous at different values of $\ln(\bar{r}_i)$: each doctor will respond in the same way (Callaway et al., 2024). This is a stronger parallel trends assumption than in the case of a binary treatment. However, since we cannot observe the counterfactuals, we cannot directly test for parallel trends (Callaway et al., 2024; Roth, 2022). We provide suggestive evidence from an event study where in equation 1 we replace $post_t$ with a set of year dummies, with 2014 (pre-reform) as the base year. We could have used year-quarter dummies, but these may have insufficient power compared to year dummies (Roth, 2022). In addition, we also dichotomize mean revenue into the bottom quartile (=0) and the top quartile (=1) and run an event study to provide additional evidence of parallel trends where the bottom quartile serves as the 'control' group.

Doctor fixed effects (α_{ij}) control for time invariant unobserved factors that influence the primary outcome variables and doctors' propensity to work in private practice, including specialty differences in the propensity to work in private practice (surgeons typically spend more hours in private practice than physicians), gender, geographic location which account for population characteristics and practice costs faced by each doctor (for those who don't move), as well as fixed traits such as altruism, experience, and cognitive and non-cognitive abilities. Year-quarter dummies (γ_t) capture overall trends in the outcome variables which have seasonal components. Fixed differences in geographic areas that influence utilization and fees are captured by area fixed effects (θ_j) which are defined at the level of SA3 of the doctor's primary work location, and controls for the level of amenities that attract doctors to work there such as urban-rural, the location of hospitals and health services, the costs of renting or buying private consultation rooms, and also capture broad characteristics of the population such as epidemiology, density and socio-economic status. These are defined at the SA3 level, which is larger than a postcode, with population sizes ranging between 30,000 and 130,000 people.

There may have been unobserved doctor characteristics that vary over time, influencing doctors' responses to demand shocks not captured by fixed effects; however, we believe this is unlikely. We only include doctors who did not change their primary place of work and who were qualified non-GP specialists for the entire period.

We conduct an exploratory heterogeneity analysis of the main results by running the regression on different sub-samples of the data. We explore whether surgeons are affected differently from doctors in medical (non-surgical) specialities, as surgeons typically perform more procedural work in private hospitals and have higher earnings. They could experience the highest falls in utilization, but also respond more strongly to maintain their earnings. We also examine if the results differ by doctor sex. There is evidence that female doctors respond differently to competition and so may react differently. We also examine if results vary according to specialists' self-reported level of agreement with the statement "*The majority of my patients have complex health and social problems*", with the following response categories: strongly agree/agree equal to 1 and zero otherwise. Doctors treating more complex patients tend to have higher costs and may have lower profit margins compared to those treating less complex patients, which may make them more likely to respond. We also hypothesize that specialists facing more competition might be more likely to respond. We examine this across two groups: the bottom and top 50 percent percentiles of the number of specialists per 10,000 population. We also use the number of specialists practising in the same primary specialty at an alternate address within a 5km radius as a robustness check (this has a smaller sample size).

In MABEL we have data on personality traits and risk aversion. We expect doctors who are more conscientious to be more likely to respond to a fall in demand. This hypothesis is based on evidence showing how conscientiousness is positively associated with productivity across a range of occupations (Edin, Fredriksson, Nybom, & Öckert, 2022). MABEL uses the 15-item Big Five Personality Inventory (BFI) (Goldberg, 1990; John & Srivastava, 1999; John OP, 1991) which includes five personality traits: agreeableness, conscientiousness, extraversion, neuroticism, and openness. Conscientious individuals describe themselves as orderly, systematic, inefficient (reversed), sloppy (reversed), disorganized (reversed), and efficient. Scores are standardized and we use the top and bottom 50 percent percentiles.

Finally, we expect risk-averse doctors to have a stronger compensatory reaction to the fall in demand. The risk attitude measures included in MABEL are self-report measures which are valid measures when compared to using gambles in surveys (Dohmen et al., 2011). The domain-specific MABEL Risk Attitudes Scale was developed by adapting the Risk Propensity Scale proposed by Nicholson *et al.* (2005) to the context of physician behaviours and has been previously used to examine prescribing decisions (Mendez, Scott, and Zhang 2021; Zhang, Méndez, and Scott 2019) and has been shown to be relatively stable over time (Zhu, van der Pol, Scott, & Allan, 2023). The measure asks physicians about their willingness to engage in risk-taking activities on a scale from zero (very unlikely) to five (very likely), in three different domains: financial (e.g., investment with an uncertain outcome), career and professional (e.g., publicly challenging your professional colleagues), and clinical domains (e.g., recommending a treatment that is new to your usual practice or is controversial). We use the measure of risk-taking in the financial domain. Scores are standardized and we use the top and bottom 50 percent percentiles.

Results

The characteristics of those included in the analysis are shown in Tables 1 and compared with the population of non-GP specialists in 2015 (when consent for linkage was obtained and at baseline). The specialists who consented for linkage and included in the estimation sample are broadly similar in terms of gender and age, though are slightly older (aged between 50 and 65 years old). Specialists in the estimation sample are more likely to be surgeons, less likely to be qualified from overseas, less likely to work in a major city, more likely to work in affluent areas, less likely to be from New South Wales & the Australian Capital Territory, less likely to be from Queensland, South Australia and Western Australia (& NT), and more likely to be from Tasmania and Victoria. The sample is more representative with respect to the distribution of claims across MBS items – the pattern of items claimed for the estimation sample is very similar to all claims for all other non-GP specialists in Australia (Appendix Table A1).

We use the data from Table 1 to calculate inverse probability weights which are used in the regression analyses so the estimation sample is more representative according to these observed characteristics. Descriptive statistics of the dependent variables are in Table 2.

The main results are shown in Table 3. The coefficients in Table 3 show how those who are more exposed to private hospital work (who have 1 percent more revenue from private hospital work pre-2015) respond to a fall in demand for PHI post-2015. For total claims for in-hospital services which were directly affected by the fall in demand for PHI, doctors earning 1 percent more revenue from private in-hospital work before 2015 had 8.9 fewer claims per quarter after

2015. This is equivalent to 9.7 percent fewer claims per quarter compared to the pre-2015 median. There is also evidence that the fall in demand for PHI led to a reduction in the average MBS fee per service of $6.27 for every additional 1 percent of revenue (3.1 percent compared to the median in 2015) from working in private hospitals. This suggests a less complex and costly mix of services were being claimed post-2015. There is weaker evidence that average fees fell by $7.52 (by 2.5 percent) for every 1 percent of revenue from private hospital work.

There is no evidence of substitution of activity between private in-hospital and private out of hospital services (ie consultations). Effects on the percentage of hospital claims, hours worked in private hospitals, hours worked in private rooms, and the number of out-of-hospital claims, were all relatively small and not statistically significant. However, we do find weak evidence that hours worked in the public sector increased by 0.3 hours per week (1.7 percent). We can approximate the marginal rate of substitution between reductions in in-hospital MBS items and increases in hours in public hospitals. For every MBS item reduction per quarter, hours worked in public hospitals increased by 0.4 hours (24 minutes) per quarter ((0.299 hrs per week x 12 weeks per month = 3.59 hrs per quarter, divided by 8.9 = 0.4 hrs per quarter).

We find only weak evidence of spillover effects to out-of-hospital services consistent with trying to maintain revenue. Total revenue from private out of hospital work fell by $992 per doctor per quarter (4.8 percent) for every additional 1 percent of private hospital revenue before 2015 but this was not statistically significant. There is evidence of higher bulk billing of out-of-hospital consultations of 1.21 percentage points (or 3.1 percent relative to the pre-2015 median) after 2015 for doctors who were more exposed to working in private hospitals. This suggests doctors were choosing to reduce fees for some patients to help stimulate demand. This is confirmed by evidence that the average fee charged also fell by $1.46 (0.09 percent) but this effect is small and not statistically significant. However, event study plots (Appendix 1 Figure A) cast doubt over pre-2015 parallel trends for out of hospital bulk-billing so the result of a 1.21 percentage point reduction should be interpreted with caution.

The average MBS fee was $1.53 (1.3 percent relative to the median) higher for doctors who had 1 percent higher revenue pre-2015. This suggests that doctors were claiming for a slightly more expensive mix of consultations, which can be interpreted as upcoding of claims or selecting a more profitable mix of patients. Upcoding is the most likely explanation because we also find that doctors with higher pre-2015 private hospital revenue were not seeing more complex patients after 2015[3]. The number of doctor-initiated follow-up consultations increased but this effect was small and not statistically significant.

Event study plots for each dependent variable are shown in Appendix 1 Figure A1. This shows the effect on outcomes of a 1 percent increase in mean pre-2015 private hospital revenue in each year (we aggregated quarters to years for clarity), relative to 2014 (the vertical line in each chart) the year before demand starts to fall. For the key results in Table 3 which are statistically significant, these plots generally support the assumption of parallel trends. The exception is for bulk billing for out-of-hospital services where there is evidence that the average marginal change in pre-2015 revenue is different from zero.

Table 4 shows the results when quartiles of pre-2015 mean revenue are used, with quartile 1 as the base (omitted) category so results are relative to this. These results are generally supportive of the main results in Table 3. For most outcome variables, doctors with pre-2015 private revenue in the highest quartile 4 were more likely to change their behaviour than those in lower quartiles. In Appendix Table A2 we also show event study plots where quartile 1 is compared to 4. This provides further evidence supporting parallel trends for most outcomes that were statistically signifcant in Table 3, comparing the bottom and top quartiles of the distribution of pre-2015 mean revenue from working in private hospitals.

The main effects of the fall in demand reported in Table 3 vary by doctor characteristics. Figure 1 shows heterogeneity for the results for in-hospital services, those directly affected by the fall in demand for PHI. Looking down each column shows the extent to which each outcome was driven by specific groups of doctors. For example, the fall in total claims per doctor per month was apparent across all sub-groups of doctor characteristics, apart from being driven more by male than female doctors. The fall in the average MBS fee we observed in the main results seems to be driven more by doctors in medical specialties, doctors who are less conscientiousness and who are more risk averse. There is some evidence that those in areas of low density of other

[3] We ran a regression with patient complexity as the dependent variable, and β was -0.004 and not statistically significant.

specialists were more likely to reduce the number of hours spent working in private hospitals. The increase in hours spent working in public hospitals is driven mainly by male doctors, who are risk-loving, and possibly have more complex patients overall. For each comparison (eg surgical vs medical, female vs male) and for each outcome, all confidence intervals overlap suggesting there are no differences in outcomes between each group category. For example, male doctors are no different to female doctors in how they respond across all outcomes.

For out-of-hospital services, though the overall effect at the mean in Table 3 is relatively small and not statistically significant, there is evidence that those who are highly conscientious, risk-loving, and possibly in an area of high doctor density were more likely to experience a fall in claims for out of hospital consultations, supporting the finding of no volume offsets between in-hospital and out-of-hospital claims. There is weak evidence that those who are risk-lovers experience lower revenue for out of hospital services. There is weak evidence that average fee per service fell for surgeons, supporting the evidence of higher bulk billing rates on average. The increase in bulk billing in Table 3 was driven by male medical specialists with low conscientiousness, high risk aversion, and possibly less complex patients and in areas of lower doctor density (notwithstanding issues with parallel trends for this outcome). The increase in the average MBS fee, which we argue reflects upcoding of claims, was driven by male doctors with low conscientiousness, possibly high patent complexity, and low doctor density.

Discussion

This paper examines the effect of a fall in demand for voluntary private health insurance on the supply of physician services. Just as insurance expansions can lead to increases in utilization, a fall in demand can lead to falls in utilization. We find evidence that the fall in demand for private health insurance led to a fall in utilization for privately insured in-hospital services and a less complex mix of in-hospital services being provided. The fall in complexity of in-hospital services was driven by risk-averse doctors in non-surgical specialties who may have been less likely to treat costly and complex patients. There was weak evidence that doctors compensated for the fall in demand by increasing the number of hours working in public hospitals and reducing fees for in-hospital services. We found weak evidence that doctors compensated for the fall in in-hospital private services by reducing the price (increasing bulk billing) for out-of-hospital services, though for this outcome parallel trends did not hold. This was driven by risk-averse males with low conscientiousness who were from non-surgical specialties and located in areas of lower doctor density. In addition, there was evidence of compensatory behaviour by doctors by claiming more complex and costly out-of-hospital services, which we interpret as upcoding. The overall effect was small but was again driven by males with low conscientiousness and located in areas of low doctor density. They maintained revenue by (possibly) reducing prices to help stimulate demand and upcoding of claims. Across several outcomes male doctors with low conscientiousness, from non-surgical specialties, with high risk aversion and in areas of low doctor density (less competition) seemed more likely to be affected.

The general magnitude of the effects on in-hospital utilization are reasonably large: an almost 10 percent reduction in claims for private in-hospital care. The compensatory effects are, however, not as strong as one might expect. There is no large volume offset in either in-hospital activity or out-of-hospital activity. There is no evidence that doctors reduced the number of hours worked in private hospitals. Compensatory responses to maintain revenue were focussed on upcoding.

Generally, those with voluntary PHI in Australia have higher utilization of hospital care than those without, even though on average they have lower need (Cameron et al., 1988; Cheng, 2014; Doiron & Kettlewell, 2018; Eldridge et al., 2017) but effects from these studies are from survey data and are not causal. The only other study to examine a reduction in demand for voluntary private health insurance simulated the effect of a reduction in the premium subsidy and found that a 25 percentage point reduction in the rebate subsidy would lower insurance coverage by 1.8 percentage points, and this would lead to a 2.49 per cent and 2.33 per cent reduction in private day and overnight admissions (Cheng, 2014). Our design and results do not allow a direct comparison with this simulation, though our findings are consistent with it.

Our identification strategy relies on the assumption that physicians with higher private revenue pre-2015 do not systematically differ in ways that affect their responsiveness to demand shocks, such that treatment effects should be homogenous. We control for doctor fixed effects and area fixed effects that might influence the amount of private revenue, and parallel trends for most outcomes are supportive. There may have been unobserved doctor characteristics that vary over time that influence doctors' response to demand shocks not captured by fixed effects, but we think this is unlikely. We only include doctors who did not change their main location of work and who were qualified non-GP specialists for the whole period.

A limitation is that the claims data do not include patient identifiers or characteristics, so our results reflect changes in activity and billing at the doctor-level. We cannot examine changes to the intensity of services per patient. However, our analysis does show that a doctor self-reported measure of patient complexity did not change after 2015. We also control for doctor and area fixed effects which would account for differences in patient complexity between doctors that do not vary over time. In addition, our sample of specialists is small. However, we find they are representative of the population of specialists in terms of the mix of services they provide, but less so in terms of their observable characteristics, which we adjust for in all analyses the analysis using inverse probability weights. This does not account for differences in unobservable characteristics between consenting doctors and the population. A key issue with difference-in-difference analyses with a continuous treatment is difficulty in interpreting the results and bias if the continuous treatment also includes 'level' treatment effects from those with a zero dose (Callaway et al., 2024). However, we avoid this problem as we do not have data on 'zeros' of private sector revenue – those doctors who worked only in the public sector.

A key issue we are unable to fully explore is the impact of the reduced utilization of private hospital services on public hospital admissions. We find that for every MBS item reduction per quarter, hours worked in public hospitals increased by 0.4 hours (24 minutes). This is based on weak evidence that doctors increased their working hours in public hospitals using self-reported data on hours worked and we have no data on the utilization of public hospitals for people who dropped their PHI cover. The self-reported data on hours worked, have, however, been reported to be similar to data from larger scale surveys with close to 100 percent response rates (Szawlowski et al., 2020).

At the time of the reduction in demand for PHI, there was strong rhetoric from the PHI sector about the adverse impact it could have on public hospitals and waiting times. This argument has been consistently used to support the introduction and continuation of government subsidies for PHI. Further research needs to explore if this fall in the utilization of private hospitals led to an increase in demand for public hospital care or waiting time, or whether the reduction in utilization was for low-value care.

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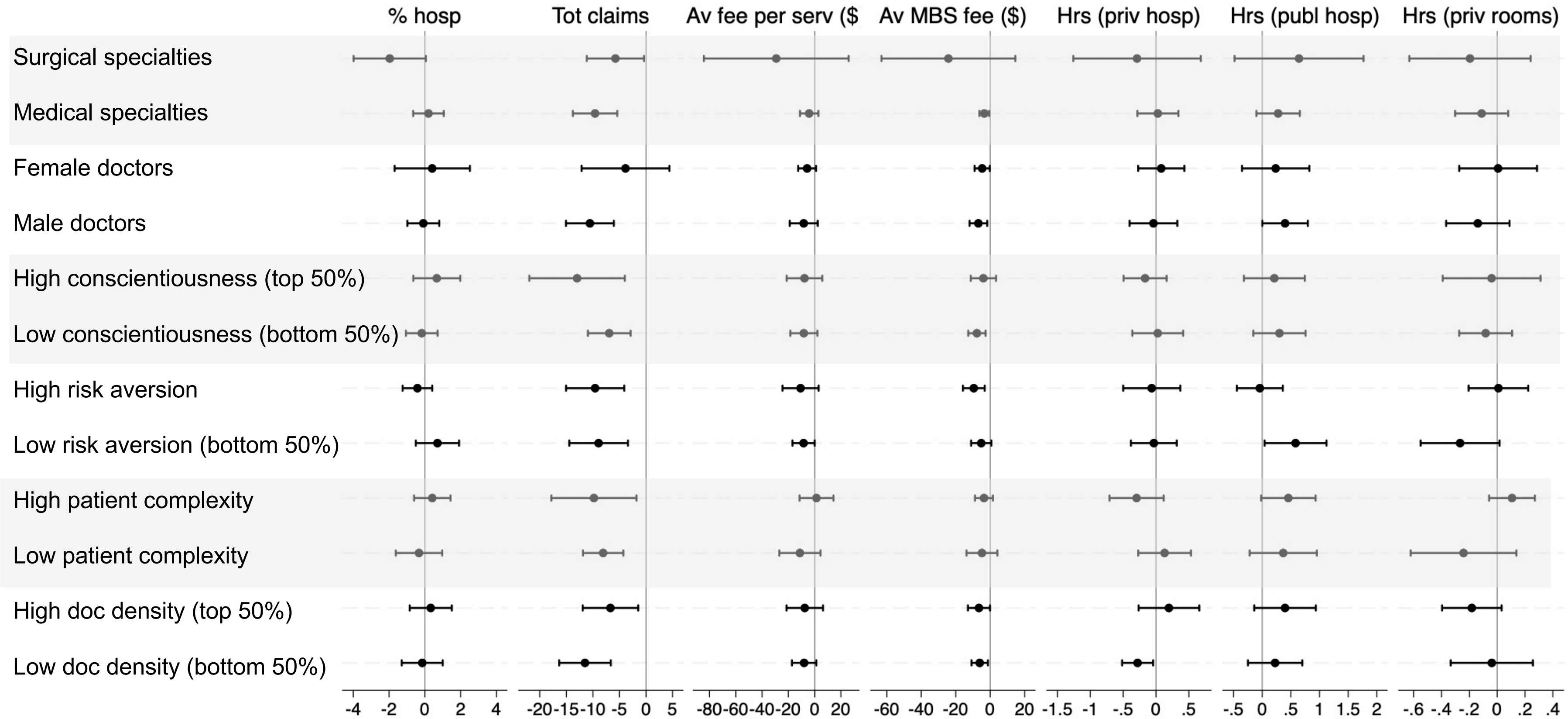
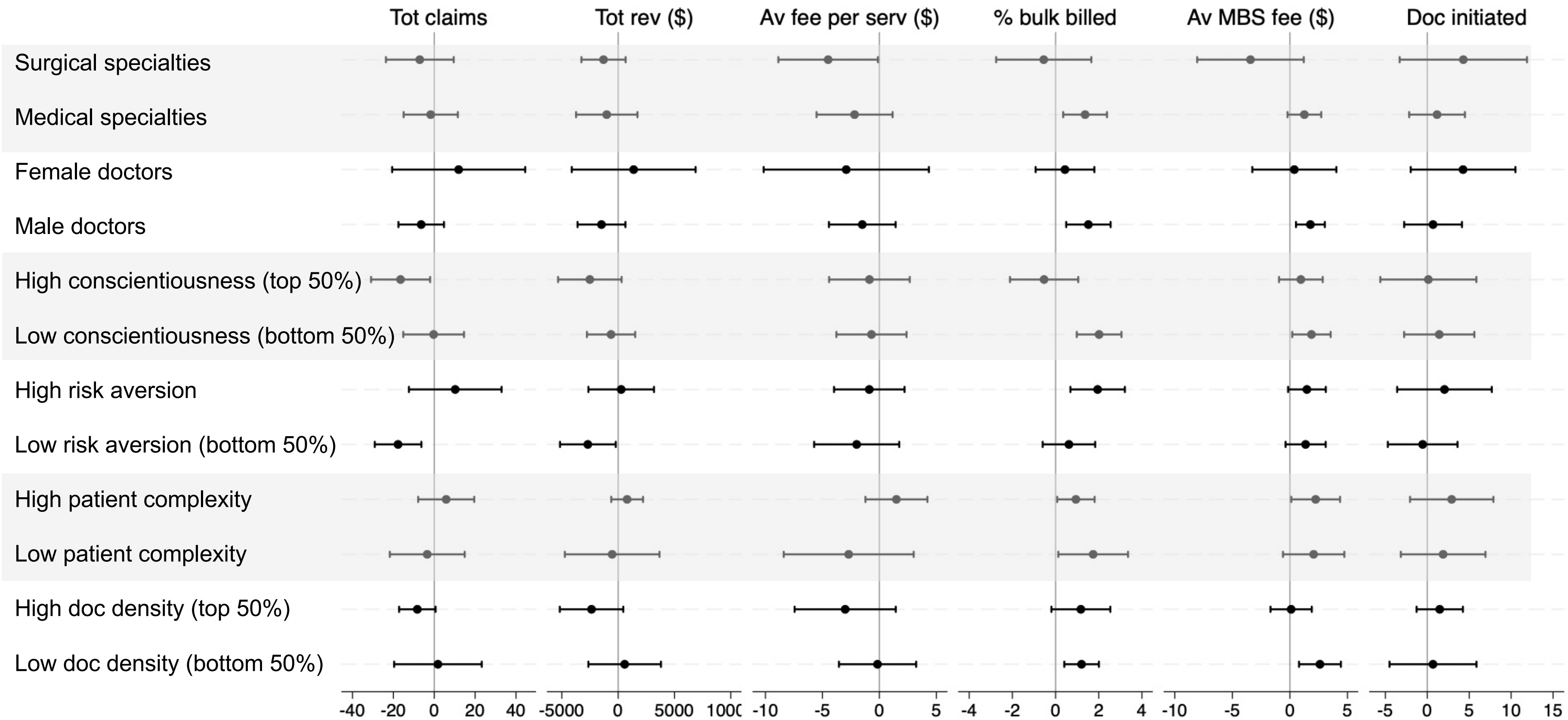
Figure 1. Heterogeneity in main results across doctor characteristics: in-hospital services (point estimate and 95 per cent confidence intervals)



Notes: each point estimate presents the results from a single regression model of the same specification as in equation 1 (Table 3) but estimated on each particular sub-sample defined by the characteristics. The confidence intervals test the hypothesis that $\beta \neq 0$ for that sub-group. Overlapping confidence intervals for sub-groups (eg between male and female) show that the difference in the point estimates between groups are not statistically significant.

Figure 2. Heterogeneity in main results across doctor characteristics: out-of-hospital services (point estimate and 95 per cent confidence intervals)



Notes: each point estimate presents the results from a single regression model of the same specification as in equation 1 (Table 3) but estimated on each particular sub-sample defined by the characteristics. The confidence test the hypothesis that $\beta \neq 0$ for that sub-group. Overlapping confidence intervals for sub-groups (eg male and female) show that the difference in the point estimates are not statistically significant.

Table 1: Descriptive statistics and comparison of estimation sample with population in 2015 (n = 25,733)

	Population			Estimation sample		
	Mean/Prop	SD	n	Mean/Prop	SD	n
Male	0.734	0.442	25145	0.718	0.451	588
Female	0.266	0.442	25145	0.282	0.451	588
Surgeon	0.151	0.358	25145	0.191	0.394	585
Qualified overseas	0.278	0.448	24473	0.224	0.417	577
<40 yrs old	0.117	0.321	24929	0.079	0.270	584
40-44 yrs old	0.166	0.372	24929	0.161	0.368	584
45-49 yrs old	0.164	0.370	24929	0.151	0.358	584
50-54 yrs old	0.152	0.359	24929	0.156	0.363	584
55-59 yrs old	0.131	0.338	24929	0.171	0.377	584
60-64 yrs old	0.101	0.301	24929	0.144	0.351	584
65+ yrs old	0.169	0.375	24929	0.139	0.346	584
Major City	0.867	0.340	24778	0.779	0.415	588
SEIFA quartile 1	0.289	0.453	24749	0.310	0.463	588
SEIFA quartile 2	0.152	0.359	24749	0.189	0.392	588
SEIFA quartile 3	0.395	0.489	24749	0.361	0.481	588
SEIFA quartile 4	0.165	0.371	24749	0.141	0.348	588
NSW & ACT	0.341	0.474	25145	0.279	0.449	588
QLD	0.188	0.391	25145	0.189	0.392	588
SA	0.081	0.273	25145	0.068	0.252	588
VIC & TAS	0.283	0.451	25145	0.391	0.488	588
WA & NT	0.107	0.308	25145	0.073	0.261	588

Notes: Population includes all non-GP specialists in clinical practice in 2015 from Medical Directory of Australia (Australasian Medical Publishing Company). Some States combined due to small numbers in estimation sample. SIEFA is a measure of economic disadvantage with quartile 1 being the least disadvantaged.

Table 2. Descriptive characteristics (means across all quarters) of dependent variables from the estimation sample (15,120 observations, 588 doctors)

	Mean/Prop	SD	10th Perc.	50th Perc.	90th Perc.	n
Percent hosp claims	52.32	38.68	5.53	43.12	100.00	15120
Total claims: hosp	179.44	242.56	8.00	87.00	467.00	15120
Average fee per service: hosp ($)	460.84	484.61	120.15	285.40	1102.37	14830
Average MBS fee: hosp ($)	286.80	249.04	106.17	185.30	631.30	14830
Hours worked (private hosp)	10.18	12.34	0.00	6.00	27.00	14683
Hours worked (public hosp)	20.52	17.70	0.00	17.50	45.00	14758
Hours worked (private rooms)	11.34	13.80	0.00	4.00	30.00	14577
Total claims: out of hosp	343.22	508.38	0.00	161.62	916.29	15120
Total revenue: out of hosp ($)	51445	98738	0.00	17345	136561	15120
Average fee per service: out of hosp ($)	178.65	160.55	89.51	148.82	276.99	11245
Percent bulk billed: out of hosp	50.26	38.57	4.05	41.58	100.00	11245
Average MBS fee: out of hosp ($)	128.59	74.93	74.64	110.90	189.63	11245
Number of doc initiated out of hosp	139.22	164.70	0.00	93.00	340.00	11245
Majority of patients have complex health and social problems	0.58	0.49	0.00	1.00	1.00	14774

Table 3: Regression results

In-hospital services	Percent of hosp claims	Total claims	Average fee per service	Average MBS fee	Hours worked (private hosp)	Hours worked (public hosp)	Hours worked (private rooms)
Post x ln(mean revenue pre-2015), β	0.075	-8.900***	-7.519*	-6.273***	-0.015	0.299*	-0.111
Median of dependent variable (pre-2015)	42.71	92.00	298.69	200.05	6.00	18.00	5.00
Observations	15120	15120	14830	14830	14681	14756	14575

Out-of-hospital services	Total claims	Total Revenue ($)	Average fee per service ($)	Percent bulk billed	Average MBS fee ($)	No. of doc initiated out of hosp
Post x ln(mean revenue pre-2015), β	-3.300	-992.137	-1.457	1.214***	1.529**	1.088
Median of dependent variable (pre-2015)	196.81	20595	152.18	39.46	117.06	101.00
Observations	15120	15120	11223	11223	11223	11223

Notes: Ordinary least squares regressions with doctor, time, area fixed effects.

Table 4. Regression results: quartiles

In-hospital services	Percent of hosp claims	Total claims	Average fee per service	Average MBS fee	Hours worked (private hosp)	Hours worked (public hosp)	Hours worked (private rooms)
Post x Q2	3.375*	-11.248**	-3.080	-1.548	-0.153	2.271***	0.057
Post x Q3	0.134	-14.804**	13.740	-3.389	0.862*	0.719	-0.098
Post x Q4	-0.438	-41.197***	-30.893*	-25.465***	-0.344	1.965**	-0.323
Observations	15120	15120	14830	14830	14681	14756	14575
Out-of-hospital services	Total claims	Total Revenue ($)	Average fee per service ($)	Percent bulk billed	Average MBS fee ($)	No. of doc initiated out of hosp	
Post x Q2	4.664	-2811	1.181	2.490*	5.777	7.774	
Post x Q3	0.390	-7609	-9.274	2.502**	1.621	12.599*	
Post x Q4	-3.977	-2663	-5.358	5.052***	6.458**	3.626	
Observations	15120	15120	11223	11223	11223	11223	

Notes: Ordinary least squares regressions with doctor, time, area fixed effects. Results show quartiles of pre-2015 mean revenue from working in private hospitals. Unlike Table 3, mean revenue is not logged.

Table 5. Heterogeneity analysis

In-Hospital services	Percentage of hosp	Total claims	Average fee per service	Average MBS fee	Number of hours worked (private)
Medical specialties	-0.152	-9.729***	-3.069	-3.158**	0.040
Surgical specialties	-2.489**	-5.240**	-35.396	-28.097	-0.158
Male doctors	-0.630	-10.931***	-5.715	-5.815**	-0.026
Female doctors	0.099	-4.734	-7.055*	-4.717**	0.046
High conscientiousness (top 50%)	0.836	-14.751***	-2.929	-1.033	-0.050
Low conscientiousness (bottom 50%)	-0.567	-6.850***	-8.300	-7.767***	0.028
Low risk aversion (top 50%)	-1.008*	-10.279***	-8.854	-9.225***	-0.078
High risk aversion (bottom 50%)	0.399	-8.818***	-6.964	-4.253	0.012

Out of hospital services	Total claims	Total Revenue	Average fee per service	Percent bulk billed	Average MBS fee	Number of doc initiated out of hosp
Medical specialties	1.878	-61.742	-0.664	1.159**	1.310	1.282
Surgical specialties	-2.392	-765.423	-4.985**	-0.866	-4.011	6.085
Male doctors	-2.742	-826.802	0.115	1.348**	2.037**	0.525
Female doctors	15.748	2173.221	-4.687	0.777	-0.738	5.765
High concientiousness (top 50%)	-19.694**	-2660.397	0.270	-1.045	1.047	-2.985
Low concientiousness (bottom 50%)	2.486	-267.850	0.010	1.907***	1.599	2.753
Low risk aversion (top 50%)	20.151	1508.109	0.186	2.121***	1.327*	4.698
High risk aversion (bottom 50%)	-19.536***	-2621.430*	-1.528	0.059	1.357	-2.343

Appendix 1.

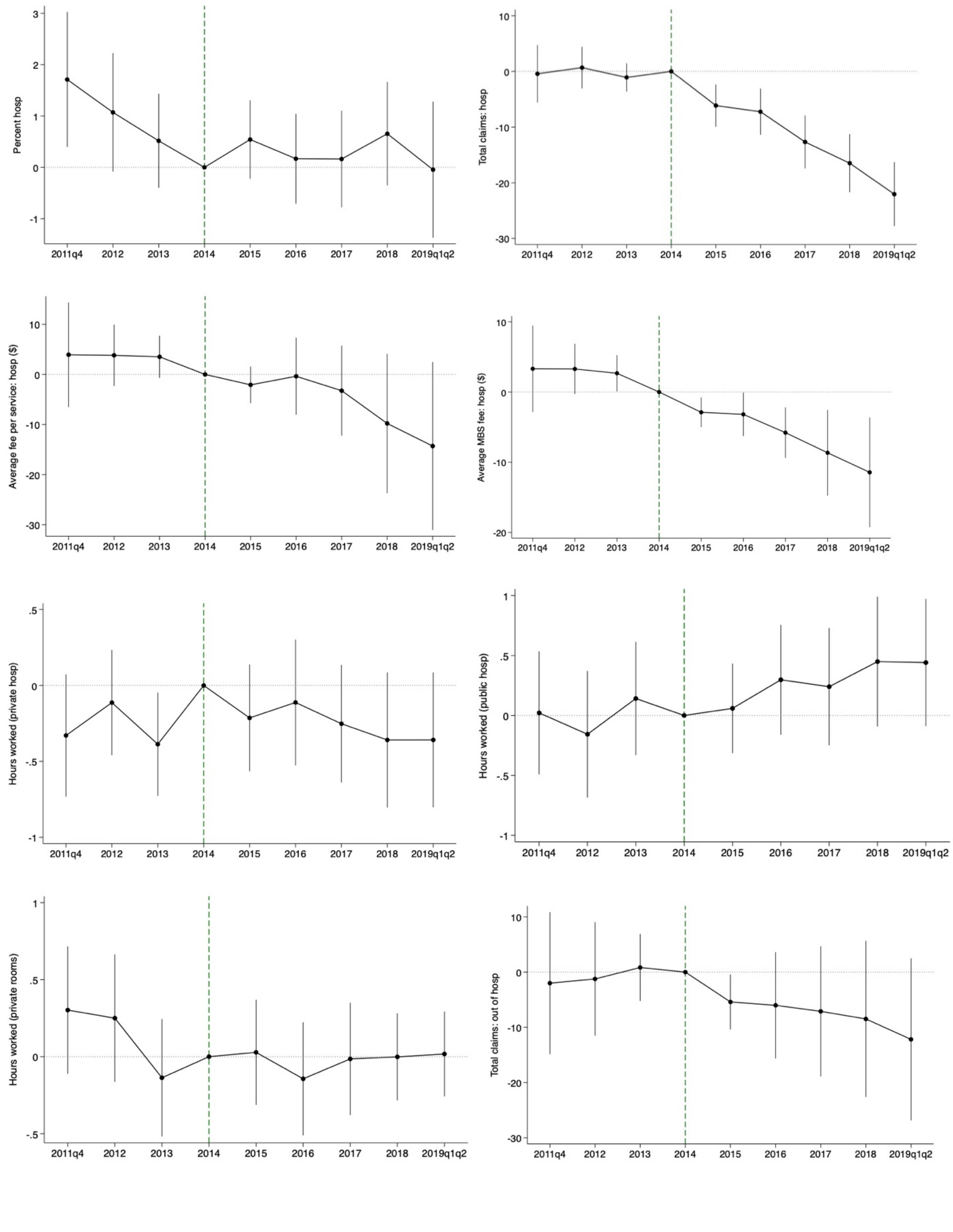
Representativeness

Table A1. Number and distribution of claims in 2015 (Non-GP specialists)

	Sample (n, %)	National (n, %)
A4 Consultant Physician (other than psychiatrist)	374,120 (24.8)	12,203,499 (22.0)
A3 Specialist Attendances	348,541 (23.1)	11,605,214 (20.9)
T8 Surgical Operations	239,481 (15.9)	9,977,475 (18.0)
T1 Miscellaneous Therapeutic Procedures	103,126 (6.8)	3,075,373 (5.5)
T10 Relative Value Guide for Anaesthesia	92,290 (6.1)	2,879,802 (5.2)
T6 Anaesthetics	84,593 (5.6)	2,568,242 (4.6)
T4 Obstetrics	80,918 (5.4)	1,942,613 (3.5)
A8 Consultant Psychiatrist	58,774 (3.9)	2,290,696 (4.1)
T2 Radiation Oncology	57,478 (3.8)	1,988,754 (3.6)
A2 Other non-referred	32,528 (2.2)	5,567,290 (10.0)
A24 Pain and Palliative Medicine	8,522 (0.6)	159,997 (0.3)
T9 Assistance at Operations	7,262 (0.5)	490,081 (0.9)
T7 Regional or Field Nerve Blocks	5,998 (0.4)	338,323 (0.6)
T11 Botulinum Toxin Injections	4,472 (0.3)	54,570 (0.1)
A26 Neurosurgery Attendances to which no other item applies	3,958 (0.3)	225,898 (0.4)
A21 Medical Practitioner (Emergency Dept, private hospital)	3,128 (0.2)	96,162 (0.2)
A28 Geriatric Medicine	1,771 (0.1)	47,286 (0.1)
A30 Medical Practitioner video conferencing	1,145 (0.1)	34,901 (0.1)
A29 Early Intervention Services for Children	606 (<0.1)	10,257 (<0.1)
A5 Prolonged	406 (<0.1)	18,008 (<0.1)
T3 Therapeutic Nuclear Medicine	121 (<0.1)	4,014 (<0.1)
A27 Pregnancy Support Counselling	88 (<0.1)	8,682 (<0.1)
A13 Public Health Physician Attendances	44 (<0.1)	6,965 (<0.1)
A9 Contact Lenses	34 (<0.1)	369 (<0.1)
C2 Oral Surgical Services	8 (<0.1)	547 (<0.1)
	1,509,412	55,595,018

Source: MABEL-MBS linked data, and Medical Directory of Australia, doctors in clinical practice. Excludes diagnostic imaging and pathology as the national data do not distinguish which type of doctors made the claim.

Figure A1. Event study plots before and after the fall in demand.



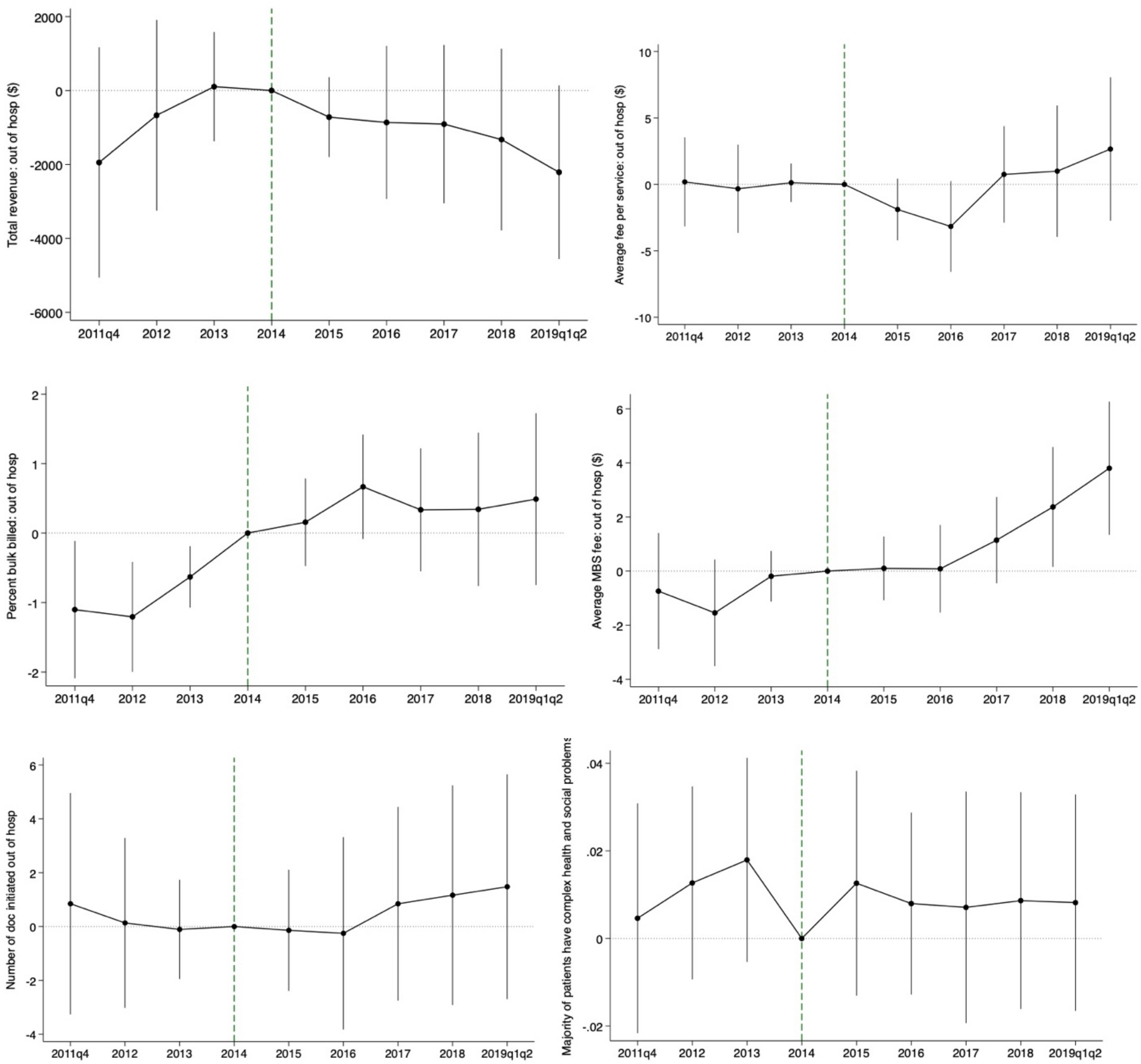
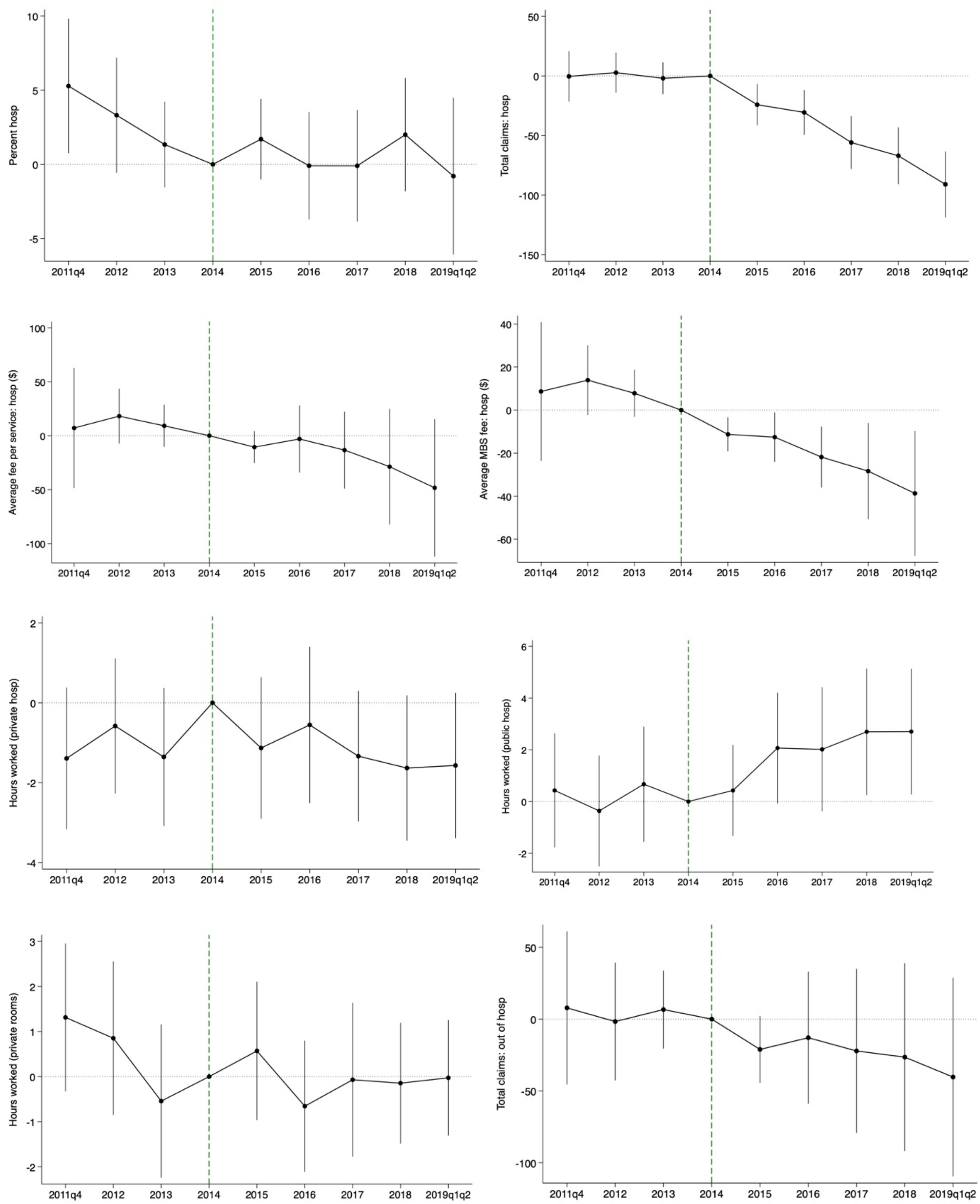
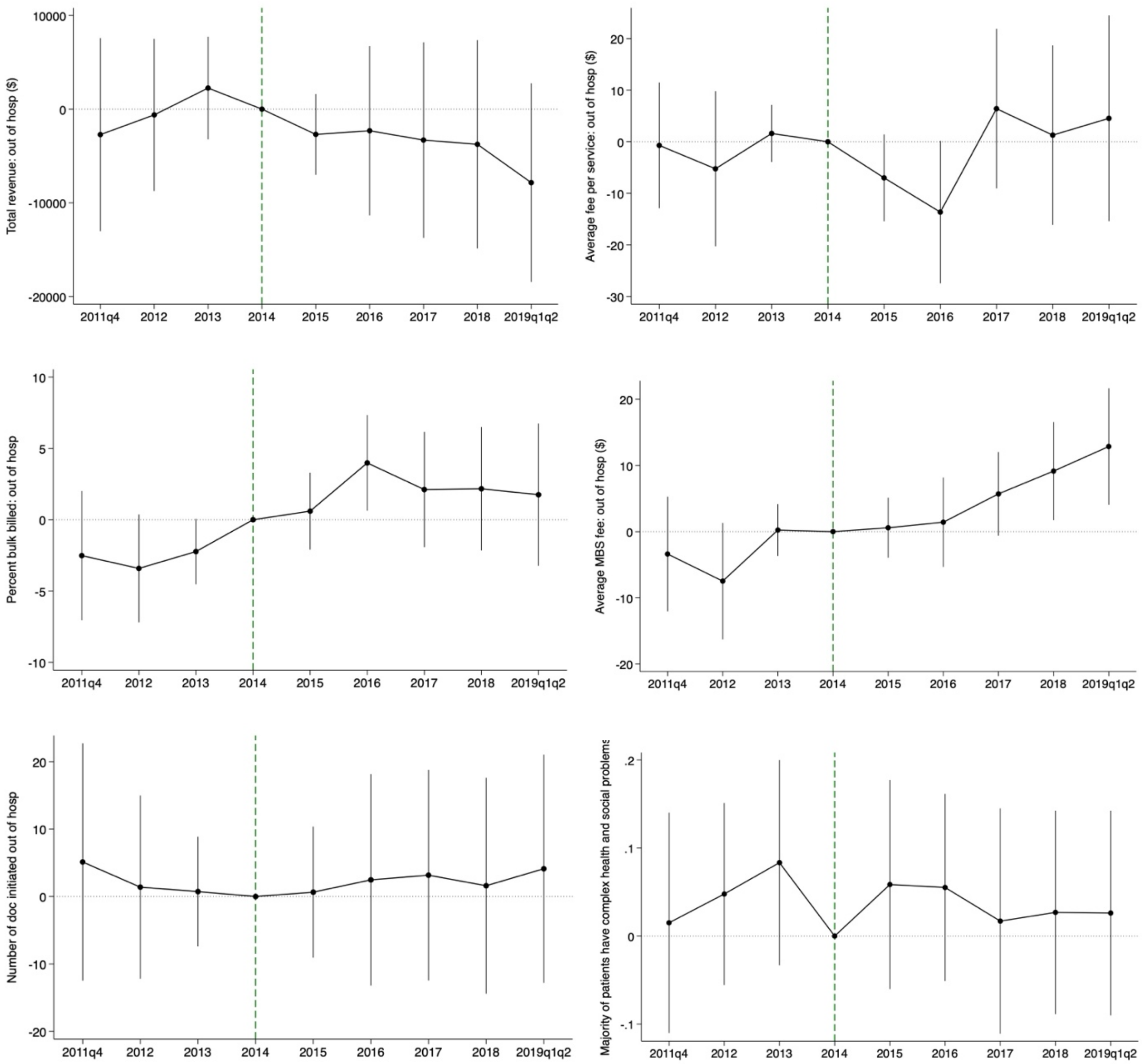

Total revenue: out of hosp ($)
2000
0
-2000
-4000
-6000
2011q4
2012
2013
2014
2015
2016
2017
2018
2019q1q2
Average fee per service: out of hosp ($)
10
5
0
-5
-10
Percent bulk billed: out of hosp
2
1
0
-1
-2
Average MBS fee: out of hosp ($)
6
4
2
0
-2
-4
Number of doc initiated out of hosp
6
4
2
0
-2
-4
Majority of patients have complex health and social problems
.04
.02
0
-.02

Figure A2. Event study plots before and after the fall in demand comparing quartile 4 with quartile 1 of the distribution of pre-2015 mean revenue.




Total revenue: out of hosp ($)
Average fee per service: out of hosp ($)
Percent bulk billed: out of hosp
Average MBS fee: out of hosp ($)
Number of doc initiated out of hosp
Majority of patients have complex health and social problems
2011q4
2012
2013
2014
2015
2016
2017
2018
2019q1q2