Prescribing cost-effective treatments under financial constraints in the English National Health Service*

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Abstract

Medical innovations and improvements in healthcare have contributed to large improvements in welfare but also growing healthcare costs. At the same time, financial constraints in public sector institutions may affect the delivery of services. We examine whether hospital trusts with budget deficits prescribe new, cost-effective but expensive treatments for Hepatitis C differently. This is especially important since Hepatitis C is a communicable disease, and its treatment yields long-term benefits. We compile a novel panel dataset of hospital trusts providing acute care in England, linking detailed data on financial statements, workforce statistics, prescribing volumes, hospital activity, and quality of care. We employ two complementary identification strategies: two-way fixed effects and an instrumental variables approach, using historical deficits and hospital activity in large disease groups as instruments for current financial positions. Our findings indicate that hospitals in worse financial positions prescribe fewer treatments: a 10% increase of a standard deviation in a trust's surplus (£2 million) is associated with a 1.7-2.7% increase in prescribing new Hepatitis C medicines. We rule out several potential mechanisms, including staff composition, drug costs, and quality of care.

Keywords: healthcare budgets, cost-effectiveness, prescribing, public health

JEL Codes: I18, I11, H51

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1 Introduction

The delivery of quality public services is subject to financial constraints. Negative income shocks to the public sector can impact the ability of local governments to provide public services (Feler and Senses, 2017). However, publicly-owned enterprises may respond to lower relative incomes by either improving productivity or sustaining chronic losses with the expectation of a bailout (Bohn, 1991; Song et al., 2012). Depending on how binding their budget constraint is, governments may provide additional funding, debt relief or other compensations (Lin and Tan, 1999; Bertero and Rondi, 2000; Kornai et al., 2003). In healthcare, hospitals are also known to respond to financial incentives (Duggan, 2000; Acemoglu and Finkelstein, 2008) and there is evidence that negative credit shocks can affect the quality of care hospitals deliver (Gaynor et al., 2015; Aghamolla et al., 2023).

Medical innovations and improvements in healthcare have contributed to large improvements in welfare but also growing healthcare costs (Becker et al., 2005; Lo and Thakor, 2023). At the same time, there are growing financial pressures on healthcare budgets with increases in demand. Following several years of austerity politics in the United Kingdom, the expenses of healthcare providers began to routinely outstrip incomes resulting in a historical record of deficits in 2015 (Lafond et al., 2015; Dunn et al., 2016). This is attributed to growth in demand and staff costs with acute care providers facing a disproportionate financial burden, as treatments in secondary care are also the most expensive (Lafond et al., 2015).

In this paper, we investigate whether financial constraints of hospitals affect the prescribing of cost-effective but expensive new medicines. Our observational units are secondary care health providers known as 'trusts' in the English National Health Service (NHS), which comprise one or more hospitals under one management. Our sample covers 62 autonomous hospital trusts that prescribe innovative Hepatitis C medicines. We assemble an extensive novel panel dataset linking quarterly data from 2015 to 2018 on prescribing with financial accounts including staffing levels and drug costs, hospital episode statistics on activity, and hospital quality data on mortality.

We focus on Hepatitis C, whose treatments benefited from medical innovations with high efficacy. New direct-acting antivirals (DAA) became available for use in the English NHS in 2015, representing effective cure for the majority of patients (McConachie et al., 2016; Pecoraro et al., 2019). Concerns emerged that despite the technological availability of new medicines to treat Hepatitis C, they may not be affordable for the health system (Public Health England, 2015). Differential access to medicines via different drug prices, credit constraints or insurance patterns have real health impacts (Chandra et al., 2021). Despite the long-term welfare benefits of some new medicines, health providers with deficits may not prescribe them given their financial constraints if these medicines are very expensive.

Both in the United States and in the United Kingdom, the there were discussions about the excessive costs of the new Hepatitis C treatments (Chhatwal et al., 2015; Najafzadeh et al., 2015; Henry, 2018). Just one pill of Sovaldi – the commercial name of the compound Sofosbuvir – costs approximately USD$1,000, which brings the total cost of the twelve-week treatment to USD$84,000. In the United Kingdom, upon introduction, Sovaldi's cost to the NHS was about £35,000 per treatment (Pharmaforum, 2014). The approval for use in the UK resulted in concerns that this would mean a £700 million bill for NHS (Hawkes, 2015; Lomas, 2019). However, it is not clear whether financial constraints would have had any impact on prescribing as the NHS made funding for Hepatitis C patients available through 'specialised commissioning', in effect guaranteeing the reimbursement of drug costs (NHS England, 2015).

We measure financial constraints of hospitals using the balance of operating expenses and income, as reported in the trusts' financial accounts. To estimate how prescribing Hepatitis C patients may be affected by deficits of healthcare providers, we use two complementary identification strategies: i) panel two-way fixed effects, controlling for provider-specific time-invariant factors and common time shocks and ii) an instrumental variables (IV) strategy to account for the potential endogeneity of the operating surplus/deficit using two sets of instrument groups. We instrument current financial positions with lagged deficits as well as

with hospital activity in large disease groups. As continuous deficits accumulate the financial costs to hospitals through debt servicing, previous deficits likely impact current financial positions. Activity in large disease groups, which require repeated care and expensive treatments may contribute to higher costs for some providers (Briggs et al., 2018; Bhatnagar et al., 2015). We apply adaptive Lasso to select the relevant instruments from a large set of potential hospital activity categories (Zou, 2006; Windmeijer et al., 2019).

Our main results indicate that a 10% standard deviation (SD) increase in the trust's surplus (about £2 million) is correlated with 1.7% increase in prescribing of the new medicines for Hepatitis C. These results are robust to alternative estimations with varying the definition of the independent and the dependant variable, additional controls, sample restrictions and clustering strategies. We find that it is only the contemporaneous value of the surplus/deficit that impact prescribing. Applying our IV strategy, the findings show that current financial positions are correlated with their lags and the Lasso IV selects diseases of the circulatory system as one of significant predictors of surplus/deficits. The point estimate we obtain is larger at 2.7% increase in prescribing. The larger estimate of the IV in this context implies hospital providers, which have consistently run deficits are even less likely to prescribe the new medicines.

To explain what drives the results, we analyse a range of alternative mechanisms and conduct mediation analysis to quantify how much of the total effect is direct and mediated (Imai et al., 2010; Hicks and Tingley, 2011). One hypothesis is that trusts with higher deficits would be able to hire less of the key staff groups, have higher drug costs or different quality level of care. As staffing expenses are major drivers of operating expenses, we investigate whether staff composition, for instance having more doctors or scientific staff is correlated with operating deficits (Lafond et al., 2015). However, we do not find that staff composition in the period 2015-2018 can be explained by the trusts' financial positions or that staffing levels can explain prescribing. We also look at drug costs as well as hospital quality as captured by the mortality indicators and similarly rule out that the impact is mediated

through either of those channels.

Our paper contributes to the literature on budget decisions under financial constraints (Anderson et al., 2012; Lomas, 2019) with an empirical application using a panel data structure, where previous work provides theoretical modelling or is not able to identify the impact of budget deficits (Akinleye et al., 2019). We do find that financial constraints are relevant in healthcare provision even when in theory the drug bill for the new medicines is subject to complete reimbursement (Duggan, 2000; Acemoglu and Finkelstein, 2008; Aghamolla et al., 2023). As such, our results point to 'a hard budget constraint', where overall deficit may be impacting the provision of services that may not be considered as directly affected (Bertero and Rondi, 2000; Kornai et al., 2003).

We navigate complex public health data sources with changing definitions and varying degrees of data quality, to assemble an extensive and new dataset. Our empirical strategy uses an application of an adaptive Lasso IV approach for instrument selection in a setting with a high-dimensional set of potential instruments (Zou, 2006; Chernozhukov et al., 2015; Windmeijer et al., 2019). This approach is specifically suited for our context where large disease groups activity is named as contributing to higher expenses but specific definitions and methods were lacking. We do find that the Lasso IV and the IV deliver very similar results and reinforce the conclusions of our OLS two-way fixed effects analysis.

Our paper is also related to the literature of financial incentives and fiscal externalities (Finkelstein, 2004; Lin and Sacks, 2019; Starc and Town, 2020), giving an example of how rigid rules of funding allocation may not fully capture the benefits of adopting new technologies. We give evidence from a public health system 'free at the point of delivery', where financial questions provoke public debate about the fair allocation of funds. Our analysis speaks to the question of how to design well-functioning, fair and optimal funding schemes in health care (Burau et al., 2018; Lundkvist, 2002; Schmitz, 2013; Duggan, 2005). Our findings emphasise the need to consider the adverse impacts, which financial deficits cause on public services delivery.

The rest of this paper is organised as follows. First, section 2 describes the background and the institutional context, setting out in more detail the regulatory and policy environment facing hospital trusts in the English NHS and providing context about the Hepatitis C patient population and the recent medication innovations. Then, section 3 describes the data sources alongside key summary statistics on all variables in the analysis. Section 4 sets our empirical strategy with the OLS two-way fixed, the IV strategy, tests the identifying restrictions, and presents the results. Then, section 5 investigates the mechanisms that may explain these results through a mediation analysis, and section 6 provides some discussion and finishes with concluding remarks.

2 Background and institutional context

In this section, we provide context on the funding framework of the English National Health Service (NHS) and how health providers adopt and receive reimbursement for new, cost-effective medicines. The introduction of a new class of innovative medicines to treat Hepatitis C in 2015 coincided with a year of record financial deficits and unprecedented financial pressure on the public health system. Concerns about their affordability followed. However, the NHS made special funding available with a reimbursement mechanism that ensured providers received the full drug cost of treating Hepatitis C patients.

2.1 Hospital trusts in deficit

During the period of austerity politics in England beginning in 2010, National Health Service hospital trusts' spending routinely exceeded income. NHS providers and commissioners ended 2015/16 with an aggregate deficit of £1.85 billion, a threefold increase on the previous year, thus recording the largest aggregate deficit in NHS history (Dunn et al., 2016). Mainly, the acute trusts have felt this financial pressure with operating expenses growing twice as fast as incomes (Lafond et al., 2015) and by 2018/19, providers of acute care still had an

aggregate deficit of £1.23 billion (The King's Fund, 2022). The increasing financial pressures on the acute sector partly reflect increasing demand for care with rising costs for staffing, the largest single area of spending for NHS providers: the staffing pay bill accounting for almost two-thirds (Lafond et al., 2015). In general, the growing pressures on the public health system also identify technological change as on of the key driver of increasing costs (Sorenson et al., 2013; de Meijer et al., 2013; Santana et al., 2020).

2.2 Cost-effective treatments

The NHS needs to evaluate the value for money of new medicines and whether they should be prescribed for patients in the public health system. The National Institute of Care and Excellence (NICE) developed the overall framework and clinical guidelines for innovative new drugs. When a new medicine becomes available, NICE evaluates its cost-effectiveness (Collins, 2020), and recommends those that offer good value for money for use in the NHS. If the medicine offers one Quality Adjusted Life-Year (QALY) per £30,000 spent, then it is deemed cost-effective. QALYs are units of standardised health, which reflect the quantity and quality of life years added with new treatments or medicines. The treatments, recommended by NICE in its technology appraisal programmes, must be funded by the NHS, as mandated by law, through the 'funding directive'. However, whether a treatment is prescribed largely depends on the prescriber as providers have relative autonomy.

NICE recommends new treatments based on the national reference price of the treatments. However, trusts group together regionally to purchase drugs from suppliers. This price can vary from between trusts based on different procurement strategies. Any contract prices agreed through a framework between the drug companies and the government remain confidential and are not disclosed to the public. NICE requires hospital trusts to make funding available for treatments it recommends for use, but hospital trusts are also penalised for running significant deficits. The NHS spent £19 billion on medicines in 2018/19, amounting to about 15% of the total budget of the NHS. Hospital use accounted for more than half of

that cost (Ewbank et al., 2018).

2.3 Payments to hospital trusts

Hospital trusts in England primarily receive funding through a mechanism known as the National Tariff Payment System (NTPS). Hospitals' payments come through three main methods: the national tariff, block contracts (fixed sum paid to a provider for delivering a service over a given period), and central commissioning of specialised services. Under the national tariff, trusts receive reimbursement for the volume of activity they undertake based on a set of national prices for the healthcare activities or procedures.

Services that are only provided in a few hospitals due to their specialised nature – for instance rare cancers, genetic disorders or complex medical or surgical conditions – are often directly commissioned and paid for directly by NHS England. For instance, Hepatitis C treatment falls under the purview of 'specialised service commissioning' because it involves complex and specialised care, including the provision of antiviral medications and ongoing monitoring of patients (NHS England, 2015). The reimbursement for Hepatitis C treatment follows the submission of a Blueteq form for each patient treated and in principle, the NHS provider should receive reimbursement for the cost of the prescribed medicine.

2.4 Innovative treatments for Hepatitis C

In 2015, new antiviral medicines were approved for use in the English NHS (see Table 1). Direct acting antiviral agents (DAAs) act by directly inhibiting viral replication independently from the immune system. For example, a 12-week course for chronic Hepatitis C medicine based on the latest treatments available costs approximately to £35,000 (Pharmaforum, 2014). In 2015, there were concerns that despite the technological availability of new medicines to treat Hepatitis C, these may not be affordable for the health system (Public Health England, 2015; Lomas, 2019). In June 2015, the NHS announced a single largest investment in new treatments: the budget was increased to £190 million for new

virological cures for Hepatitis C, from the approximately £40 million in the previous year (NHS England, 2015).

Pricing of new medicines is often linked to the health benefits they generate, and thus new medicines that generate significant health benefits can be very expensive. These higher prices may not be affordable in the short-term if providers are required to meet set budgets and are not able to account for the dynamic health benefits of new treatments (Henry, 2018; Lomas, 2019).

Table 1: Technological appraisals (TA) guidance approval dates

Treatment	Date Approved	Appraisal
sofosbuvir	Feb-15	TA330
dasabuvir	Nov-15	TA365

2.5 Hepatitis C background

Hepatitis C is an infectious disease that affects the liver, and if untreated, can cause life-threatening liver damage (Shepard et al., 2005). It is spread through blood-to-blood contact, it is often asymptomatic and there is no vaccine that can prevent its transmission (Poynard et al., 2003). Most Hepatitis C infections spread through sharing unsterilised needles used for injecting recreational drugs (can be also transmitted through sharing razors and toothbrushes). The majority of infected persons are from marginalised and under-served groups, including people who inject drugs (PWID), with about 50% of PWIDs estimated to be infected (Public Health England, 2015).

With the latest antiviral medications, more than 95% of people with Hepatitis C may be cured. Following the introduction of the new direct-acting antivirals (DAA) medicines in 2015 (McConachie et al., 2016; Pecoraro et al., 2019), there has been a substantial increase in the number of treatments initiated – patients accessing treatment – as well as a decline in the patient population and the associated Hepatitis C mortality. In England, treatment ini-

tiations rose from about 6,400 per year during 2014-2015 to 15,400 in 2019-2020 (UK Health Security Agency, 2022). Similarly, the estimated patient population has steadily declined. In 2015 there were an estimated 129,000 adults chronically infected with Hepatitis C in England (equating to 0.4% of the adult population). Since then, there was a substantial decline – to 81,000 in 2020 (UK Health Security Agency, 2022). As Hepatitis C is a communicable disease, reducing its prevalence generates greater benefits in the longer term as it reduces the patient population.

3 Data

3.1 Data sources

We combine data from several sources, including official statistics, aggregate administrative data, the financial accounts of trusts, and restricted-access, patient-level administrative data. We build a panel of NHS hospital trusts at the quarterly level. Our dependent variable is the prescribing volume with quarterly variation, and similarly hospital activity also comes with quarterly frequency. Our main independent variable – the annual financial accounts – as well as the staff levels and the quality indicators have annual frequency.

First, we extract financial and staffing levels information from the annual Foundation Trust Consolidation (FTC) accounts published by NHS England (NHS Monitor, 2015). It is based on a common template requested by NHS Improvement (previously known as Monitor), consolidating accounting information about the NHS providers. We use the operating surplus/deficit, the surplus/deficit for the year (resulting from adding the net finance costs), operating income and expenses in key categories and average staffing numbers the providers report. As the main independent variable in our analysis, we use the operating surplus/deficit, as it nets operating income from patient care activities, other operating income and operating expenses like provision of services, employee expenses, clinical and general supplies and services, transport, premises, drug costs and others. In the period 2015-2018,

we observe consistently the financial accounts of 80 NHS foundation trusts providing acute care.

Second, we use Pharmex published statistics on hospital purchases of innovative medicines (NHS Digital, 2015b), measured in prescribed volumes. This data contains utilisation of new, cost-effective medicines which were recommended for use in NHS England by NICE technology appraisals. Only these innovative medicines are reported in statistics supplied by NHS Digital's Innovation Scorecard. The publication of prescribing data is part of a policy that aims to improve transparency within the NHS of NICE-recommended treatments and their availability at a local level within trusts. Pharmex covers about 95% of the hospital trusts. Although there may be a delay between purchase and dispensing or supply of the product, hospitals would not usually hold significant quantities of product in their inventories. Our dataset covers prescribing of new Hepatitis C treatments between 2015 and 2018. It was first in 2015 that prescribing for Hepatitis C within Pharmex was recorded for the first time. 62 NHS foundation trusts report prescribing Hepatitis C medicines in the 2015-2018 period.

Third, to capture hospital activity, we use data from Hospital Episode Statistics (HES) published statistics (NHS Digital, 2015a). This data is published at the monthly level and is organised according to the taxonomy International Classification of Diseases 10^{th} Revision (ICD-10 codes). In order to capture hospital activity for Hepatitis C patients, we also use restricted-access, individual-level hospital episodes statistics for all patients who have been diagnosed with Hepatitis C as a first or second diagnosis and aggregate these at the level of hospital provider per quarter to match with our prescribing data. As only admitted patients would be captured in this data, once we match it with the prescribing dataset, we find that only a subset of our prescribing data has recorded hospital activity. This shows that HES data does not completely reflect the flows of patients through the secondary care system with a Hepatitis C diagnosis, as referred outpatients may not be recorded in the HES statistics. The majority of the referrals for treatment come from primary care (43%) with another 25% from general medicine, gastroenterology, or infectious diseases; then 20.4% from drug

services and prisons (Harris et al., 2019).

Fourth, to capture time-variant, provider-specific hospital quality, we use the Summary Hospital-level Mortality Indicator (SHMI). The SHMI is the ratio between the actual number of patients who die following hospitalisation at the trust and the number that would be expected to die on the basis of average England figures, given the characteristics of the patients treated there. It is a proxy rather than a direct measure of quality (NHS England, 2023).

Fifth, we use primary care prevalence data for testing the exogeneity of large disease prevalence to the Hepatitis C populations, which is collected via the Quality Outcomes Framework (QOF). We use the prevalence component of this publication. This data captures the number of diagnosed patients with the certain condition, relative to all registered patients who could have this condition. We also control for prevalence of the diseases at the trust level by linking the GP prevalence data, aggregated at the Integrated Clinical Boards (ICB) geographies and match them to the trusts within these ICB boundaries. The ICB health geographies were set up to replace Clinical Commissioning Groups (CCGs) as the main primary care commissioning authorities in 2022 and reflect a more consistent picture of health geography boundaries.

3.2 Descriptive statistics

The summary statistics are reported in Table A2, where Panel A-D describe the variables extracted from the financial accounts of the providers. The 336 observations correspond to a total of just over 80 providers observed over four years (2015-2018). The average operating financial position is £3.3 million deficit, which is a 2% deficit relative to the operating income. Figure 1 shows the distribution of surplus/deficit over provider, sorted in ascending order. Sub-figure 1a) reflects the average surplus/deficit and 1b) shows the average surplus/deficit as a percent of operating income. More than half of the providers have an average deficit over the four year period. We standardise the operating surplus/deficit variable for an easier

interpretation of the magnitudes.

The map in Figure B1 shows the regional distribution of surplus/deficits as percent of operating income where darker areas reflect higher surplus, grouped in ten quantiles of all trusts reporting accounts in the 2015-2018 period. Areas in the South a better financial position over this period. We also note that there are some areas with no NHS foundation trusts reporting financial accounts and not all of the 80 NHS foundation trusts prescribe Hepatitis C medicines. Figure B2 shows the between variation, expressed as the density of the annual operating surplus/deficit with a fairly similar distribution across the four years.

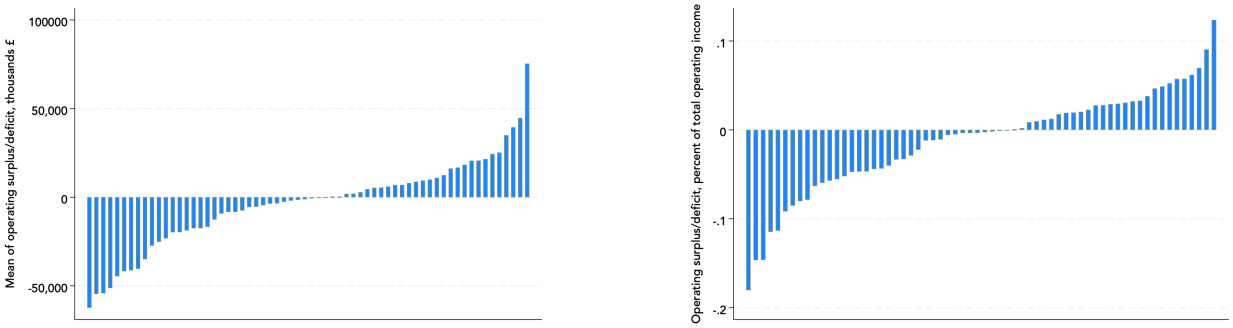
The largest operating expenses category is staff accounting for an average of 72% of the operating expenses, clinical supplies and drug costs come at an average of 11% each, followed by premises (5%) and then general supplies and services with 2%. We will use the operating expenses as robustness controls as they are time-variant across providers.

In Panel D of Table A2, we present the average staffing numbers as percent of the total staff. The largest staff group are nurses, midwives and health visitors with over one third of total staff, followed by administration and estates with 22%, healthcare assistants and support with 18% and scientific, technical and therapeutic staff with 12% as well as the doctors also with 12% and lastly healthcare science with 2%. The relative staff mix corresponds to the workforce composition of the NHS as we observe it in January 2015 (see Figure B3). We note in Figure B4 that the largest variation is within the healthcare assistants and other support. We test whether the different staffing levels may be a mechanism which can mediate the impact of the surplus/deficit as hospitals may adjust their staffing relative staff levels given needs higher financial constraints.

There are two medicines prescribed for Hepatitis C over the 2015-2018 period: dasabuvir and sofosbuvir with 80% prescribing led by dasabuvir. Panel E of Table A2 shows the numerator and the denominator summary statistics of our prescribing dataset, where the numerator's units are mg(s) per 100,000 FCE day hospital care and the numerator's units are FCE day hospital care. An FCE represents a continuous period of care under one

consultant, and each is specified with a start and an end date. We use natural logarithm of the prescribing volume as our main dependent variable, pooling together both medicines in our baseline estimation. The variation of prescribing is at the quarterly level.

Figure 1: Distribution of operating surplus/deficit, sorted in ascending order



(a) Average surplus/deficit over provider

(b) Surplus/deficit as % of operating income

Panel F of Table A2 shows that the average mortality is close to 1, namely a parity for the average trust between the actual number of patients who die following hospitalisation and the number that would be expected to die based on the predicted characteristics of the trusts' patient populations. This is a variable we use in the mechanisms analysis to proxy the quality of healthcare provision. Then, Panel G and H of Table A3 shows the summary statistics of the HES data in counts of FCEs and also in percentages of total activity for the provider in that period. Using restricted-access to individual-level HES data, we aggregate total FCEs with Hepatitis C diagnosis at the quarterly level to march our other activity data, and we find that Hepatitis C activity is not recorded in all hospitals that prescribe Hepatitis C, as possibly so patients are not admitted overnight. When we plot the average Hepatitis C activity over time (see Figure B5), we note that there has been a decline in HES Hepatitis C activity, which is consistent with the declining prevalence as noted in the more recent monitoring reports (UK Health Security Agency, 2022).

Further, Table A4 presents the descriptive statistics on the exogeneity analysis of prevalence at the primary care level. The unit of observation there is a GP practice over the same 2015-2018 time period. The prevalence variable is the number of diagnosed patients in the

practice denominated by the relevant patient population, which could have the disease. Hypertension has the largest prevalence with an average of 14% of GP practices having patients with a hypertension diagnosis. Also, an average 7% of primary care patients have a diabetes diagnoses. Additional to the GP and year fixed effects in the exogeneity analysis, we use controls for the demographic profiles of the practices that we capture with the proportions of male/female patients within age groups, which we also report in Panel M of Table A4.

Aggregating prevalence from the GP level within the ICB boundaries, we map the large disease groups in Figures B6, B7 and B8. We observe that most of the cardiovascular prevalence is lower in the regions of London and South Central, compared to the North and South West. Similar patterns are also notable in the prevalence of high dependency diseases with a clear North-South divide in diabetes and palliative care.

4 Empirical strategy

To estimate how the deficits of healthcare providers may affect prescribing, we use two complementary empirical strategies. First, we apply two-way fixed effects to explain prescribing in a hospital trust per quarter, within a medicine class. We control for time-invariant, unit-specific factors that include regional variations in healthcare demographics, levels of multiple deprivation and also unit-invariant, unobserved common shocks that affect all trusts simultaneously.

Second, we use an instrumental variables (IV) approach where we instrument budget deficits with i) the historical financial position of the healthcare providers, as well as ii) activity in large disease groups. We find that current deficits are strongly correlated with deficits in previous periods. Additionally, we also use activity in all disease groups as instruments, applying an IV and Lasso approach for the high-dimensional set of potential instruments.

In particular, the high dependency diseases (HDD) and cardiovascular disease (CVD)

exert significant pressure on the healthcare budgets (Briggs et al., 2018; Bhatnagar et al., 2015), so it is plausible that hospitals which register higher levels of activity these large disease groups may have a disproportionate disease and healthcare financial burden. The Lasso IV identifies diseases of the circulatory system as a relevant disease group which is correlated with the operating surplus/deficit.

4.1 OLS two-way fixed effects

When estimating the relationship between deficits and prescribing in a simple linear framework, the usual OLS estimation is subject to some unobserved confounders. It is less plausible that there is reverse causality, as the Hepatitis C patient population is relatively small and unlikely to affect budgets. It is, however, possible that there are unobserved factors, correlated both with prescribing as well as with budgets. In the first step of our analysis, we use the panel structure to obtain a baseline estimate of the relationship.

In Equation 1, we explain variation in the level of prescribing by the operating surplus/deficit of the healthcare provider, accounting for a number of possible unit-specific as well as time-specific unobserved heterogeneities. We note that within the catchment areas of hospitals there is relatively constant demographic composition and, similarly, macroeconomic conditions and public policies present common time-variant shocks.

$$\ln(Prescribing)_{ijqt} = \beta \cdot std(OperSurplusDeficit)_{it} + X'_{iqt}\gamma + \alpha_i + \delta_q + \theta_j + \epsilon_{ijqt} \qquad (1)$$

The dependent variable is the prescribing volume per quarter q for a provider i, for a particular Hepatitis C medicine j. The main independent variable of interest is the standardised operating surplus/deficit of a provider i in a year t, as financial accounts are available at annual frequency. Controls in X_{iqt} include total activity in all conditions as measured by finished consultant episodes (FCEs) and standardised operating income. These capture the activity and size of the healthcare providers in two alternative ways: either as volume of

treated patients or as revenue for the provided services. Subsequently, as controls we also include the operating expenses constituting the largest shares as described in Section 3.2.

In robustness, we also include staffing levels as additional controls, as well as Hepatitis C activity as measured by hospital admissions with Hepatitis C diagnosis (restricting the sample to only Hepatitis C admitted patients). Equation 1 also includes fixed effects α_i for providers, δ_q for quarters and θ_j for the different Hepatitis C medicines (dasabuvir/sofosbuvir). In the baseline, we cluster standard errors at the provider level and, for robustness, we present alternative clustering strategies.

The key identification assumption is that the fixed effects fully capture the unobserved heterogeneity differentiating healthcare providers and there are no time-variant unit-specific factors, which correlate both with financial position of trusts as well as with prescribing. As Hepatitis C hospital prescribing data is available only for the medicines that became available in 2015, we cannot verify the identification assumption with an event study of parallel trends. In the robustness section, we present a placebo test for future forward values of surplus/deficit and rule out that they affect contemporary prescribing.

4.1.1 OLS FE results

Table 2 presents the main results of estimating Equation (1), where all columns use the natural logarithm of prescribing of Hepatitis C medicines as the dependent variable and include the total finished consultant episodes (FCEs) as a control for the hospital activity within that quarter. All columns also include fixed effects for quarter, provider and medicine. Column (2) adds subsequently the control for operating income and Column (3) also adds the operating expenses: staff, drugs, premises, clinical supplies and services and general supplies in services. Adding the dis-aggregation of the operating expenses accounts for potentially different costs providers face in their local input markets.

The coefficient on the operating surplus/deficit remains significant at 5% across all columns, indicating that 10% of a standard deviations (SD) increase in the surplus/deficit

Table 2: Main results OLS - Prescribing Hepatitis C medicines

Outcome:	(1) Hepatitis C prescribing	(2) Hepatitis C prescribing	(3) Hepatitis C prescribing
Std. operating surplus/deficit	0.168**	0.167**	0.152**
	(0.063)	(0.064)	(0.061)
N	565	565	565
N providers	62	62	62
Trust FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes
Control for total FCEs	No	Yes	Yes
Control for operating income	No	Yes	Yes
Control for operating expenses	No	No	Yes

Notes: Dependent variable is the natural logarithm of prescribing Hepatitis C treatments. All columns include provider, quarter and medicine fixed effects and a control for the hospital activity captured by the total finished consultant episodes (FCEs). Column (2) adds a control for the operating income and Column (3) adds also the operating expenses controls. Standard errors clustered at the provider level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

increases Hepatitis C prescribing by 1.7% in the baseline. The result is stable with the addition of the controls for the operating income, indicating that the relative size of the hospital is not driving the results. Then the addition of the separate operating expenses categories results in a slightly smaller magnitude at 1.5%.

OLS FE robustness

To test the robustness of the results, we present alternative estimations on the basis of placebo leads and lags of the operating surplus/deficit, varying the definition of the independent and the dependant variable, additional controls, sample restrictions and clustering strategies. Table A5 reports the results from the robustness analysis.

The dependent variable is the natural logarithm of prescribing Hepatitis C medicines in Columns (1)-(10) and (13)-(18), and the winsorised prescribing (not logged) in Columns (11)-(12). The first robustness considers whether lagged and forward values of the indepen-

dent variable also explain prescribing. Columns (2) and (3) add one and two leads of the operating surplus/deficit as a control, respectively. Then Columns (4) and (5) add one and two lags, respectively. Then Column (6) uses the two lags and two leads of the independent variable. We find that it is only the contemporaneous value of the surplus deficit matters for prescribing, retaining a stable magnitude, slightly larger – 2.2% – when including the full set of lags and leads. As we use lags of the independent variable as instruments, this shows evidence for our exclusion restriction.

We further vary the definitions of the independent variable and we find qualitatively similar results. Column (8) uses the percentage surplus/deficit relative to operating income as an independent variable instead of the standardised values. We find that a 1 p.p. increase in the surplus/deficit increases prescribing by 3%. Column (9) uses an indicator variable for having a non-negative operating surplus, and Column (10) interacts the standardised operating surplus/deficit with the indicator for a non-negative surplus. We ma consider that there is a disproportionate impact for a trust with a deficit vs. a trust with a surplus and the interaction specification provides a statistical test for that. We do not find that the impact of the deficit varies across the surplus/deficit distribution.

Columns (11) and (12) use the winsorised definition of prescribing at the 1% and at the 0.1% high-only values (winsorised at the top) because of outliers, where the operating surplus/deficits are standardised as in the baseline. Here a 10% SD increase in the surplus increases prescribing by 3.7-4.5 thousand mgs, which is the measurement unit of prescribing.

Further, we add additional controls and implement some sample restrictions. Column (13) uses additional controls for operating expenses as well as staffing levels and we find that the magnitude of our coefficient declines to 1.3%. When we control for prevalence at the primary care level – either for atrial fibrillation and cardiovascular disease only or for all large disease prevalence in Columns (14)-(15), our results remain significant at 5%. When we restrict the sample to prescribing for admitted Hepatitis C patients as recorded by the HES statistics in Column (16), we find qualitatively similar but smaller results (1%), which

is noisier in the smaller sample. Columns (17) and (18) restrict the sample to prescribing only for Dasabuvir or Sofosbuvir, respectively. We find that the results are driven by largely Dasabuvir.

Table A6 applies alternative clustering strategies with two-way clustering, at ICB boundaries and also at the level of health regions (East of England, London, Midlands, North, North East and Yorkshire, North West, South, South East, and South West). We report the wild-cluster bootstrap p-value for the regional clustering as there are only nine regions. Our results remain robust to changing the clustering strategies and we retain clustering at the provider level in the baseline.

4.2 Instrumental variable (IV) and adaptive Lasso-IV

The main limitation of the empirical strategy we apply in Section 4.1 is that, in the presence of time-variant unit-specific unobserved heterogeneity, the OLS fixed effects approach is not sufficient to remove potential endogeneity. Using instrumental variables (IV) we address this issue by applying two alternative approaches. First, we use the historical financial position of the healthcare providers to predict the current operating surplus/deficit. Second, we use the hospital activity across all disease groups as an alternative group of instruments, where we use adaptive Lasso to select the relevant instruments from a large set. Hospital activity in large disease groups, the high dependency diseases (HDD) and cardiovascular diseases (CVD), are considered to place substantial burden to the health system because of the large prevalence numbers and the frequent care required (Briggs et al., 2018; Bhatnagar et al., 2015).

In the first stage predict the surplus/deficits across providers:

$$std(OperSurplusDeficit)_{ijqt} = Z'_{it}\eta_{FS} + X'_{it}\gamma_{FS} + \alpha_i + \delta_q + \theta_j + u_{ijqt} \tag{2}$$

The instruments included in Z are i) the hospital episode statistics (HES) in percentages

and in counts that captures the all hospital activity and ii) two lags of historical annual surplus/deficit and operating surplus/deficit. The controls are the total activity captured in the aggregate finished consultant episodes (FCEs) and the operating income of the trust as well as the fixed effects for trust, quarter and medicine (same as in the FE OLS).

In the second stage, we use the predicted values to estimate:

$$\ln(Prescribing)_{ijqt} = \beta_{IV} \cdot std(\widehat{OperSurplusDeficit})_{ijqtt} + X'_{it}\gamma_{IV} + \alpha_i + \delta_q + \theta_j + \epsilon_{ijqt} \quad (3)$$

Financial deficits in the past may affect current deficits as debt is accumulated and impacts the available funds in the present, as deficits are carried over from previous financial years (Encinosa and Bernard, 2005; Akinleye et al., 2019).

Our identifying assumption is that the historical financial position only affects prescribing via its impact on the current operating surplus/deficit. The second instrumental variable approach tests a commonly held view in English health policy that treating some health conditions is more expensive and that hospitals that are burdened with more activity in large disease groups are worse off financially. As there is no simple measure of hospital activity in large disease groups, we use the full set of diagnostic categories for all admitted patients. As this is a large set with twenty categories, we apply a machine-learning method of partialling out adaptive Lasso IV regression, which is applicable in a context with a large number of potential instruments (Chernozhukov et al., 2015) with the optimal adaptive weights (Zou, 2006):

$$\hat{\beta}(lasso) = \arg\min_{\beta} ||\mathbf{y} - \sum_{j=1}^{p} \mathbf{x}_j \beta_j||^2 + \lambda \sum_{j=1}^{p} w_j |\beta_j| \quad (4)$$

The main objective of the Lasso variable selection is to find the relevant predictive variables amongst the large set of potential instruments. λ is a non-negative regularization parameter, where the second term in Equation 4 is the penalty and an increasing λ shrinks the parameters β_j. Zou (2006) shows that it is the adaptive Lasso, namely using adaptive

weights, which results in consistency.

4.2.1 IV results

Table 3 presents the results from the instrumental variable analysis reporting the second stage coefficients of the surplus/deficit and the relevant statistics (see the first stage Table A7 and A8 in the Appendix). As we have a large set of instruments, we may be concerned both about over-identification and also weak instruments (Andrews et al., 2019). Another issue, is that if we use the lagged values of the operating surplus/deficit as instruments, then our first stage would be subject to a dynamic panel bias (Nickell, 1981). We present therefore separate regressions where we either use both lagged versions of the operating surplus/deficit and also the lagged annual surplus/deficit or only the annual surplus/deficit. When we examine the first stage results in Table A8, we do see that indeed the negative coefficient on the lagged operating surplus/deficit speak for Nickell bias. However, the coefficient on the lagged annual surplus/deficit is positive and significant. The annual surplus/deficit accounts for all financial costs and other financial operations, which come on top of the operating surplus/deficit.

We have the baseline OLS fixed effects regression in Column (1) of Table 3 . Then, Column (2) uses only hospital activity in the instruments set and Columns (3)-(4) uses only lags of annual and the operating surplus/deficit. Then Columns (5)-(6) combine the two IV strategies adding the hospital activity and the lagged financial positions. Using only the hospital activity as an instrument set, we obtain an IV estimate that is indistinguishable from the OLS: where a 10% SD increase in the surplus/deficit increases prescribing by 1.65%. When we apply the lags as instruments as well as the hospital activity, we obtain a larger coefficient at 2.35%. One possible explanation for the OLS-IV gap is that complier trusts in this context, that have been consistently running deficits for a few years, are more careful about costs and prescribing less of the new expensive medicines. An alternative explanation based on the violation of the exclusion restriction is not plausible as the results in Columns

(2)-(6) of Table A5 showed that prescribing depends on the current decicits rather than lagged values.

Across the three columns (2), (4), (5), and (6) the standard Kleibergen-Paap Wald statistic shows a strong first stage and the Sargan J statistic of overidentifying restrictions has χ^2 p-values exceeding 10%. However, when we apply the weak IV test (Olea and Pflueger, 2013), we obtain lower F-statistics not exceeding 10. As we have a higher number of instruments than endogenous regressors and within the list of hospital activity we also have potentially irrelevant disease groups. Given that the instrument set also contains lagged values of the endogenous regressor, serial correlation is a concern and the effective F statistic is more credible. With this motivation we apply the IV-Lasso in columns (5) and (6), letting it select the relevant instruments.

Table 3: Main results IV - Prescribing Hepatitis C treatments

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Outcome: Prescribing Hepatitis C medicines							
Std. operating surplus/deficit	0.167**	0.165*	0.414***	0.265***	0.244**	0.235**	0.277***
	(0.064)	(0.098)	(0.143)	(0.098)	(0.111)	(0.106)	(0.081)
F statistic (Cragg-Donald Wald)		9.01	19.90	24.59	8.15	11.03	
F statistic (Kleibergen-Paap Wald)		33.84	3.93	49.16	58.91	321.37	
Effective F (Montiel Olea and Pflueger)		2.67	4.51	5.48	2.51	3.42	
Sargan J statistic		37	0	4	39	41	
N	565	517	527	527	476	476	476
Model:	FE OLS	IV	IV	IV	IV	IV	Lasso
Instruments: 2 lags operating surplus/deficit	No	No	No	Yes	No	Yes	Yes
Instruments: 2 lags annual surplus/deficit	No	No	Yes	Yes	Yes	Yes	Yes
Instruments: HES activity	No	Yes	No	No	Yes	Yes	Yes
Trust FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for total FCEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control for operating income	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the logarithm of prescribing Hepatitis C treatments. Column (1) implements the OLS with trust/provider FE. Columns (2) uses a standard 2SLS, predicting the operating surplus/deficit with HES activity in aggregate categories and Column (3) uses only the two lags of the annual surplus/deficit and the operating surplus/deficit. Columns (4) combines the two IV strategies. Then, Columns (5)-(6) uses lasso instrumental-variables linear regression model, adaptively selecting the value of the lasso penalty parameter lambda. Column (7) uses applies again the IV with the selected instruments from the lasso. Standard errors clustered at the level of provider. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The Lasso-IV delivers very similar results in magnitude to the IV-estimates which include the lags and select the diseases of the circulatory system as a relevant group which explains deficits. When we run the IV with the selected instruments only in Column (7), we obtain a coefficient of 2.77% The lambda selected by cross-validation is 0.217 with four non-zero coefficients, which are the two lags of the annual surplus deficit, the disease group "Factors

influencing health status and contact with health services with ICD-10 codes Z00-Z99 and Diseases of the circulatory system (I00-I99).

4.2.2 Prevalence of large diseases in primary care

In the following subsection, we test the exogeneity of large disease prevalence and consequent subsequent activity in secondary care to the relatively 'small disease' population of Hepatitis C patients. If there are some areas with higher concentrations of patients who require more care and therefore are more expensive for the health system to treat, then such areas may have deficits and subsequently prescribe less Hepatitis C medicines. We can conduct analysis of prevalence using primary care data, which we assemble in order to test the assumption of the prevalence exogeneity.

In Equation 5, we investigate to what extent the prevalence of Hepatitis C is correlated with the large diseases. We group these into i) the cardiovascular disease (CVD) – atrial fibrillation, coronary heart disease, cardiovascular disease primary care prevention (ages 30-74), heart failure, left ventricular systolic dysfunction, hypertension, peripheral arterial disease, stroke and transient ischaemic attack and ii) high dependency diseases (HDD) – cancer, chronic kidney disease, diabetes mellitus, palliative care. It is estimated that these diseases represent a substantial burden of healthcare costs to the public health system (Briggs et al., 2018; Bhatnagar et al., 2015).

The prevalence variable is the number of diagnosed patients in the practice denominated by the relevant patient population that could have the disease. This denominator can be all patients registered in the practice or a specific demographic group, for instance all patients aged 18 or all patients aged 30-74. To analyse prevalence, it is meaningful to investigate the primary care setting, which is where patients are registered. Also the majority of referrals for Hepatitis C treatments come from primary care (Harris et al., 2019).

We observe prevalence at the primary care / GP practice level:

$$ReferralsHepC_{gt} = \beta_k \cdot \sum^{k} PrevalenceLargeDiseases_{gkt} + \alpha_g + \delta_t + X'_{gt}\gamma + \epsilon_{gt} \quad (5)$$

In Equation 5, g denotes a GP practice and t denotes a year. The dependent variable $Referrals^k_{gt}$ are referrals for Hepatitis C per GP, per year. The covariates include activity in the large disease groups: namely prevalence of high dependency diseases (HDD) and cardiovascular disease (CVD). We similarly apply GP fixed effects α_g and year fixed effects δ_t. In the time-variant controls we include: i) the demographic profiles of patients: percentage male and female of age groups in ten year intervals and ii) other diseases prevalence (asthma, chronic obstructive pulmonary disease, obesity, dementia, depression, epilepsy, mental health, osteoporosis and rheumatoid arthritis). We cluster standard errors at the GP level. In essence, we test whether practices with more cardiovascular, diabetes and cancer patients also have more Hepatitis C patients or whether these activity levels are unrelated.

Table A9 presents the results of this analysis. We do find that there is a significant correlation between the prevalence of two cardiovascular disease conditions, where these represent milder forms, primarily treated in primary care. A 1% increase in atrial fibrillation prevalence is correlated with a 0.194% increase in Hepatitis C prevalence and a 1% increase in cardiovascular disease primary care prevention (ages 30-74) is also correlated with 0.026% increase in Hepatitis C prevalence. When left untreated atrial fibrillation can result in complications and increased stroke risk (Yoon and Joung, 2018). Similarly, cardiovascular disease prevalence in the age group 30-74 is a condition, which receives treatment in primary care and if relatively more successful, these patients should be less likely to have strokes and be treated in the A&E of hospital trusts. We do not find that high dependency diseases prevalence like cancer or diabetes are correlated with Hepatitis C prevalence. While not completely exogenous, we do not find that large diseases that would be resulting in higher hospital activity are more common in the areas where Hepatitis C is more prevalent.

5 Mechanisms and mediation

In this section, we explore the evidence for mechanisms, which may explain why hospital trusts in worse financial positions prescribe less of Hepatitis C medicines. We test the hypotheses that trusts with higher deficits i) would be able to hire lower numbers of the key staff groups, which would have the knowledge to prescribe the new medicines, ii) would be facing higher drug costs, which may discourage them from prescribing new medicines, and iii) have some underlying disadvantage in terms of the quality of care they provide. As staffing expenses are major drivers of operating expenses, we investigate whether staff composition, for instance having more doctors or scientific staff is correlated with operating deficits (Lafond et al., 2015). However, we do not find that staff composition in the period 2015-2018 can be explained by the trusts' financial positions or that staffing levels can explain prescribing. We also look at drug costs as well as hospital quality as captured by the mortality indicators and similarly rule out that the impact is mediated through either of those channels.

We proceed in three stages, where we conduct a 'first stage' analysis regressing these medicating factors on the surplus/deficits, then regressing prescribing on these potential mediators and finally implementing a causal mediation analysis (Imai et al., 2010; Hicks and Tingley, 2011) where we fit the two steps together and report the average causal mediation effect (ACME).

We quantify three alternative mechanisms. First, we consider whether higher drug costs are potentially causing lower prescribing, since the cost of the new Hepatitis C medicines was a leading concern when they became available (Lomas, 2019). Second, we look at hospital mortality rates measured by the Summary Hospital-level Mortality Indicator as a proxy for quality of care, as hospitals with worse outcomes, which are under-funded or less effective may be prescribing less of these innovative medicines (Claxton et al., 2018). The SHMI is the ratio between the actual number of patients who die following hospitalisation at the trust and the number that would be expected to die on the basis of average England figures,

given the characteristics of the patients treated there. Third, we also consider staffing levels and whether the increased proportion of a specific staff group, for example doctors, nurses or technical and scientific staff may be different across trusts and whether this could explain our results.

$$\text{Mediator}_{ikt} = \beta_{1k} \cdot std(\text{OperSurplusDeficit})_{it} + X'_{it}\gamma_1 + \alpha_i + \delta_{qt} + \theta_j + \epsilon_{1ikqt} \tag{6}$$

The outcome is the mediator variable either i) the natural logarithm of drug costs (annual frequency) as reported in the annual accounts of the trusts, ii) the mortality indicator that captures whether the trust has better or worse mortality given their patients demographic profile, or iii) the staffing levels (annual frequency), also reported in the annual accounts. The staffing levels originate from the financial accounts and they are captured by the average number of employees in the major staff groups namely: Nursing, midwifery and health visiting staff/learners; Administration and estates; Healthcare assistants and other support staff; Scientific, therapeutic and technical staff; Medical and dental, and Healthcare science staff. We use the percentages of the staff groups relative to the total staff in the trust.

The independent variable is the standardised operating surplus/deficit of a provider i in year t, which has annual variation. Controls in X_{it} include operating income in all regressions. We account for provider-level time-invariant heterogeneities with the fixed effects α_i and common time shocks with quarterly fixed effects δ_{qt}. We cluster standard errors at the provider level as in our baseline regressions.

$$\ln(\text{Prescribing})_{iqt} = \beta_{2k} \cdot \text{Mediator}_{ikt} + \beta_2 \cdot std(\text{OperSurplusDeficit})_{it} + X'_{it}\gamma_2 + \alpha_i + \delta_{qt} + \theta_j + \epsilon_{2ikqt} \tag{7}$$

The dependent variable is the prescribing per quarter q for a provider i – within a particular medicine class j for a Hepatitis C. As in the mediator first stage regression, we use the same controls and fixed effects, noting that the prescribing varies across quarters and also medicine class. The identification assumption in this mediation analysis is sequential ignorability (Imai et al., 2010; Hicks and Tingley, 2011), which implies that, in the first step,

the treatment assignment – the relative financial position – is assumed to be ignorable or statistically independent of potential outcomes and potential mediators. Additionally, the second step assumes that given the actual treatment status and pre-treatment confounders, the observed mediator is ignorable. We consider that these are plausible assumptions as staffing levels and staff mix may be adjusted given financial constraints and care quality may also be impacted by budget deficits.

We present the results from the mechanisms mediation analysis in Tables A10 and A11. In the second step, where the dependent variable is prescribing, we report the average causal mediation effect (ACME), the total effect and the direct effect.

In the first step of Table A10, we do find that operating surplus/deficit is negatively correlated with the drug costs, meaning that expenditures on drugs decline with improvements in the financial position. Contrary to the intuition that hospitals with deficits would have worse mortality, we find that better financial positions are positively correlated with the mortality index. This could be the case, if hospitals running deficits are not necessarily worse hospitals, but are actually spending relatively more and having better patient outcomes on average. The Hepatitis C patient outcomes may not be even correlated with the mortality indicator of the hospital where they received treatment as the mortality risk is not immediate but rather subject to the long-term lack of diagnosis and treatment. In the second step where prescribing is the outcome variable, we do not find that either drug costs or the mortality index help predict prescribing. At the same time, the coefficient on our treatment variable remains significant at 1% and retains a similar magnitude to our OLS estimate at 1.75%-1.83% increase in prescribing following a 10% SD increase in the surplus/deficit.

We turn to Table A11, which reports the analysis of staffing levels as a potential mediator. We do not find that operating surplus/deficit is actually correlated with any of the staffing levels across the six groups. In the second step, the inclusion of the staffing levels also does not show any significant relationship with prescribing. Our treatment coefficient remains stable with a magnitude of 1.79%-1.91%. In both tables, the ACME is not significantly different

from zero and the direct and the total effect of the treatment is very similar. In summary, our mechanism analysis does not provide any evidence for these potential mechanisms.

While, we rule out staff mix, drug costs, and the quality of care as captured by the mortality indicator as mediators, there could be alternative approaches to uncovering the underlying mechanism. The drug cost is the aggregate operating expense of trusts for all drugs, yet it is not known whether higher drug costs overall also mean that trusts purchased their Hepatitis C medicines also at a higher cost. Using the staff mix information from the financial accounts is only one way of analysing staff composition and there may be some insights from analysing seniority and rank of the medical personal or speciality, which is subject to the more detailed and complex workforce statistics. Also quality of care may not be perfectly captured by the SMHI indicator. We leave these venues open for further research.

6 Conclusion and discussion

In this paper, we consider whether hospitals with larger deficits may prescribe less of new, cost-effective but expensive medicines. The case of Hepatitis C is of particular interest, as there have been recent innovations in treatment and public debate on the affordability of these new medicines, which may provide long-term benefits in effectively eliminating an infectious disease.

We combined financial accounts information on acute trusts in the English NHS with prescribing, hospital activity and quality data in the secondary care setting. We established that better financial positions result in higher levels of prescribing of the new Hepatitis C medicines. We apply a two-way fixed effects identification strategy, which we complement with IV and Lasso IV, where we instrument budget deficits with hospital activity in large disease groups and with lagged values of the financial positions. We also examined disease prevalence in the primary care and showed that higher disease prevalence of large disease

groups, which may pose a burden to hospitals (for instance stroke, cancer and diabetes) does not correlate with the small population disease prevalence of Hepatitis C. After examining three alternative mechanisms related to staff mix, drug cost and quality of care, we did not identify that any of these, in their current definitions, help explain our results.

Further research could also consider whether a higher level of prescribing resulted in better patient outcomes, as this goes beyond the scope of our current investigation. Duggan (2005) makes the point that, while expensive, new medicines may deliver health benefits that reduce the patient's demand for other health and care services, to some extent offsetting its higher price. Research investigating the impact of additional healthcare spending aims to help health technology agencies decide whether their cost-effectiveness thresholds for accepting new technologies are set at the right level (Martin et al., 2008; Lomas, 2019). Even when evaluated as cost-effective – as is the case for the medicines we investigate – some innovative medicines may not be prescribed.

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A Appendix Tables

Table A1: Acronyms

Acronym	Full name	Definition
DAA	Direct acting antiviral agents	The combination of antiviral drugs used to treat hepatitis C infections
CVD	Cardiovascular disease	A general term for conditions affecting the heart or blood vessels
FTE	Full time equivalent	The calculation of full-time equivalent (FTE) is an employee's scheduled hours divided by the employer's hours for a full-time workweek (usually 40 hours a week)
FCE	Full consultant episode	The length of a patient's stay under the care of one healthcare provider is referred to as an episode. If the patient is referred to a different healthcare provider or consultant within the same hospital, a new episode commences.
FTC	Foundation Trust Consolidation	The foundation trust consolidation (FTC) process has operated with the sole purpose of collecting the information to prepare the consolidated NHS foundation trust accounts in that year
HDD	High Dependency Diseases	These are a disease group defined in the Quality Outcomes Framework (QOF, see below) that includes diseases with high resource intensity such as Cancer, Chronic Kidney Disease and Palliative Care
HES	Hospital Episode Statistics	Hospital Episode Statistics (HES) is a curated data product containing details about admissions, outpatient appointments and historical Accident and Emergency attendances at NHS hospitals in England
HES APC	Hospital Episode Statistics Admitted Patient Care	HES APC collates data containing details about patients admitted into care only
ICB	Integrated Clinical Boards	An integrated care board (or ICB) is a statutory NHS organisation which is responsible for developing a plan for meeting the health needs of the population, managing the NHS budget and arranging for the provision of health services in a geographical area
ICD-10	International Classification of Diseases 10th Revision	ICD-10 is the 10th revision of the International Statistical Classification of Diseases and Related Health Problems (ICD), a medical classification list by the World Health Organization (WHO)
NHS	National Health Service	The National Health Service is the publicly funded healthcare system in England.
NICE	National Institute for Health and Care Excellence	Regulatory authority that appraises the cost-effectiveness of new medicines
QALY	Quality Adjusted Life-Year	A QALY is a standardised measure of health, including both the quality and the quantity of life lived.
QOF	Quality Outcomes Framework	As part of contracting of Primary Care services from GP Practices, the Quality and Outcomes Framework (QOF) aims to improve the care patients are given by rewarding practices for the quality of care they provide to their patients, based on several indicators across a range of key areas of clinical care and public health.
SHMI	Summary Hospital-level Mortality Indicator	Ratio between the actual number of patients who die following hospitalisation at the trust and the number that would be expected to die on the basis of average England figures, given the characteristics of the patients treated there.

Notes: List of acronyms and their definitions

Table A2: Summary statistics: financials, staffing, prescribing and quality

	N	Mean	StDev	Min	Max
Panel A - Financials					
Operating surplus/deficit	336	-3321.95	25554.30	-82237.21	110206.14
Surplus/deficit for the year	336	-9869.63	30922.32	-129013.00	235501.50
Operating income	336	376208.99	229630.69	0.00	1415074.00
Clinical supplies & services	336	41925.66	32893.15	0.00	186250.00
General supplies & services	336	7282.23	6366.90	0.00	39316.00
Premises expenses	336	17590.59	14877.78	0.00	86770.70
Staff expenses	336	263542.86	147129.33	0.00	931190.00
Drug expenses	336	46603.09	41936.18	0.00	227403.00
Panel B - Financials (% operating income)					
Operating surplus/deficit	333	-0.02	0.07	-0.30	0.13
Clinical supplies & services	333	0.11	0.03	0.01	0.27
General supplies & services	333	0.02	0.01	0.00	0.07
Premises expenses	333	0.05	0.02	0.01	0.12
Staff expenses	333	0.72	0.07	0.53	0.90
Drug expenses	333	0.11	0.03	0.04	0.25
Panel C – Staffing					
Nursing, health visiting	336	1919.73	1096.15	0.00	6658.00
Administration and estates	336	1221.85	683.35	0.00	4383.00
Healthcare assistants support	336	1007.30	650.77	0.00	6949.00
Scientific and technical	336	699.28	476.53	0.00	2595.00
Medical and dental	336	719.89	446.82	0.00	2541.00
Healthcare science	336	132.86	215.31	0.00	1716.00
Panel D – Staffing (% total)					
Nursing, health visiting	333	0.34	0.06	0.22	0.53
Administration and estates	333	0.22	0.04	0.07	0.32
Healthcare assistants support	333	0.18	0.08	0.00	0.41
Scientific and technical	333	0.12	0.04	0.03	0.21
Medical and dental	333	0.12	0.02	0.05	0.21
Healthcare science	333	0.02	0.02	0.00	0.12
Panel E - Prescribing					
Dasabuvir Numerator	456	322.56	984.23	0.00	19600.00
Dasabuvir Denominator	456	99.38	45.47	32.25	307.86
Sofosbuvir Numerator	120	243.71	290.88	11.20	2083.20
Sofosbuvir Denominator	120	92.16	37.17	30.52	180.25
Panel F - Quality					
SHMI value	557	0.98	0.10	0.70	1.20
SHMI banding	557	2.11	0.49	1.00	3.00

Notes: Summary statistics of all variables in the analysis. Panel A summarises the financial accounts variables in raw form and Panel B summarises them as a percent of operating income. Panel C gives the average staffing levels, also extracted from the financial accounts within the six major staffing categories and Panel D expresses them as percentages of the total staffing levels. Panel E summarises the prescribing data in thousands, where the numerator is measured in the aggregate of mg(s), the denominator is measured in FCE day hospital care for the two treatments dasabuvir and sofosbuvir. Panel F summarises the quality measures of the Summary Hospital-level Mortality Indicator (SHMI) in terms of score and also in banding form.

Table A3: Summary statistics: hospital activity

	N	Mean	StDev	Min	Max
Panel G – Disease groups					
Infectious and parasitic	518	1839.15	1772.32	0.00	8955.00
Neoplasms	518	8522.46	10027.11	0.00	52475.00
Blood, immune mechanism	518	1513.66	1569.98	0.00	8740.00
Endocrine, nutritional, metabol.	518	1209.05	1271.29	0.00	9765.00
Mental and behavioural	518	862.78	856.61	0.00	5775.00
Nervous system	518	1586.46	1933.99	0.00	11992.00
Eye and adnexa	518	2753.38	4303.84	0.00	35950.00
Ear and mastoid process	518	367.73	397.39	0.00	1840.00
Circulatory system	518	4032.04	4204.03	0.00	20605.00
Respiratory system	518	4381.66	4015.39	0.00	23400.00
Digestive system	518	8516.19	8254.29	0.00	42410.00
Skin and subcutaneous tissue	518	1422.75	1444.91	0.00	6330.00
Musculoskeletal and connective	518	4751.72	4636.05	0.00	18736.00
Genitourinary system	518	3660.25	3570.12	0.00	19845.00
Pregnancy, childbirth	518	5205.36	5673.62	0.00	24895.00
Perinatal period conditions	518	1039.04	1174.93	0.00	7700.00
Congenital malformations etc.	518	519.72	1161.64	0.00	9650.00
Symptoms, signs and abnormal	518	7168.74	6374.44	0.00	27960.00
Injury, poisoning, etc.	518	4289.84	4141.09	0.00	20675.00
Health status factors	518	4391.15	4381.50	0.00	27625.00
Hepatitis C FCEs	429	14.17	17.85	0.00	106.00
Panel H – Disease groups % total					
Infectious and parasitic	518	0.02	0.01	0.00	0.06
Neoplasms	518	0.10	0.10	0.00	0.69
Blood, immune mechanism	518	0.02	0.02	0.00	0.17
Endocrine, nutritional, metabol.	518	0.01	0.01	0.00	0.17
Mental and behavioural	518	0.15	0.29	0.00	0.97
Nervous system	518	0.03	0.04	0.00	0.36
Eye and adnexa	518	0.03	0.08	0.00	0.93
Ear and mastoid process	518	0.00	0.00	0.00	0.02
Circulatory system	518	0.05	0.08	0.00	0.74
Respiratory system	518	0.05	0.04	0.00	0.27
Digestive system	518	0.09	0.07	0.00	0.26
Skin and subcutaneous tissue	518	0.02	0.01	0.00	0.08
Musculoskeletal and connective	518	0.06	0.09	0.00	0.68
Genitourinary system	518	0.04	0.03	0.00	0.13
Pregnancy, childbirth	518	0.05	0.07	0.00	0.56
Perinatal period conditions	518	0.01	0.01	0.00	0.16
Congenital malformations etc.	518	0.01	0.02	0.00	0.23
Symptoms, signs and abnormal	518	0.15	0.18	0.00	1.00
Injury, poisoning, etc.	518	0.05	0.04	0.00	0.27
Health status factors	518	0.06	0.05	0.00	0.36

Notes: Summary statistics of all variables in the analysis. Panel G summarises the hospital activity within the ICD-10 categorisation and also adds the Hepatitis C activity extracted from the individual-level restricted-access data in the last row. Panel H presents the summary statistics of the hospital activity in terms of percentages relative to the total activity as measured in FCEs.

Table A4: Summary statistics: prevalence in primary care

	N	Mean	StDev	Min	Max
Panel I - Cardiovascular prevalence					
Atrial fibrilation	20341	0.02	0.01	0.00	0.27
Coronary heart disease	20341	0.03	0.01	0.00	0.31
Cardiovascular disease†	20341	0.01	0.01	0.00	0.60
Heart failure	20341	0.01	0.00	0.00	0.12
Left ventricular systolic dysf.	20341	0.00	0.00	0.00	0.04
Hypertension	20341	0.14	0.04	0.00	0.62
Peripheral arterial disease	20341	0.01	0.00	0.00	0.12
Stroke tr ischaemic attack	20341	0.02	0.01	0.00	0.23
Panel J - High dependency prevalence					
Cancer	20341	0.03	0.01	0.00	0.20
Chronic kidney disease‡	20341	0.04	0.02	0.00	0.30
Diabetes mellitus	20341	0.07	0.02	0.00	0.29
Palliative care	20341	0.00	0.01	0.00	0.95
Panel K - Other prevalence					
Asthma	20341	0.06	0.01	0.00	0.16
Chronic ob pulmonary disease	20341	0.02	0.01	0.00	0.18
Obesity (18+)	20341	0.10	0.04	0.00	0.35
Dementia	20341	0.01	0.01	0.00	0.64
Depression (18+)	20341	0.09	0.04	0.00	0.38
Epilepsy (18+)	20341	0.01	0.01	0.00	0.64
Mental health	20341	0.01	0.01	0.00	0.20
Osteoperosis	20341	0.00	0.01	0.00	0.09
Rheumatoid arthritis	20341	0.01	0.00	0.00	0.05
Panel M - Demographics					
All male	20328	0.50	0.03	0.28	0.96
Male 0-4	20328	0.02	0.01	0.00	0.07
Male 5-14	20328	0.06	0.01	0.00	0.58
Male 15-24	20328	0.06	0.02	0.00	0.64
Male 25-34	20328	0.07	0.03	0.00	0.34
Male 35-44	20328	0.07	0.02	0.00	0.41
Male 45-54	20328	0.07	0.01	0.00	0.27
Male 55-64	20328	0.06	0.01	0.00	0.13
Male 65-74	20328	0.05	0.02	0.00	0.24
Male 75-84	20328	0.03	0.01	0.00	0.34
Male 85plus	20328	0.01	0.01	0.00	0.43
All female	20328	0.50	0.03	0.04	0.72
Female 0-4	20328	0.02	0.01	0.00	0.07
Female 5-14	20328	0.06	0.01	0.00	0.30
Female 15-24	20328	0.06	0.03	0.00	0.45
Female 25-34	20328	0.07	0.03	0.00	0.40
Female 35-44	20328	0.06	0.01	0.00	0.14
Female 45-54	20328	0.07	0.01	0.00	0.12
Female 55-64	20328	0.06	0.01	0.00	0.11
Female 65-74	20328	0.05	0.02	0.00	0.13
Female 75-84	20328	0.03	0.01	0.00	0.18
Female 85plus	20328	0.01	0.01	0.00	0.43

Notes: Summary statistics of all variables in the analysis. Primary care prevalence of cardiovascular diseases in Panel I, high dependency diseases in Panel J, other prevalence in Panel K and demographic control variables: male/female proportions of patient lists by age groups in Panel M.

Table A5: Robustness – OLS two-way fixed effects models of prescribing Hepatitis C medicines – leads and lags (1)-(6) and alternative variable definitions (7)-(12), additional controls in (13)-(14) and sample restrictions (15)-(18)

Outcome:	(1) Hepatitis C prescribing	(2) Hepatitis C prescribing	(3) Hepatitis C prescribing	(4) Hepatitis C prescribing	(5) Hepatitis C prescribing	(6) Hepatitis C prescribing
Std. operating surplus/deficit	0.168**	0.180**	0.171**	0.169**	0.198***	0.222**
	(0.060)	(0.068)	(0.071)	(0.065)	(0.071)	(0.084)
(t+1) Std. operating surplus/deficit		0.027	0.042			0.043
		(0.050)	(0.054)			(0.068)
(t+2) Std. operating surplus/deficit			-0.010			0.035
			(0.033)			(0.040)
(t-1) Std. operating surplus/deficit				-0.005	0.011	0.056
				(0.033)	(0.037)	(0.063)
(t-2) Std. operating surplus/deficit					0.003	0.069
					(0.053)	(0.073)
N	565	538	499	546	525	467
N providers	62	59	56	59	58	52
Trust FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes	Yes	Yes	Yes
Control for total FCEs	Yes	Yes	Yes	Yes	Yes	Yes

Outcome:	(7) Hepatitis C prescribing	(8) Hepatitis C prescribing	(9) Hepatitis C prescribing	(10) Hepatitis C prescribing	(11) Hepatitis C prescribing	(12) Hepatitis C prescribing
Std. operating surplus/deficit	0.168**			0.151	45.638**	37.205***
	(0.063)			(0.121)	(18.741)	(12.625)
Operating surplus/deficit (% income)		3.126*				
		(1.572)				
Std. operating surplus/deficit (0/1)			0.392*	0.151		
			(0.209)	(0.235)		
Std. operating surplus/deficit * Surplus (0/1)				-0.035		
				(0.161)		
N	565	565	565	565	565	565
N providers	62	62	62	62	62	62
Trust FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes	Yes	Yes	Yes
Control for total FCEs	Yes	Yes	Yes	Yes	Yes	Yes

Outcome:	(13) Hepatitis C prescribing	(14) Hepatitis C prescribing	(15) Hepatitis C prescribing	(16) Hepatitis C prescribing	(17) Hepatitis C prescribing	(18) Hepatitis C prescribing
Std. operating surplus/deficit	0.129**	0.154***	0.115**	0.107	0.181***	0.158
	(0.057)	(0.057)	(0.052)	(0.067)	(0.058)	(0.138)
N	565	516	516	404	447	109
N providers	62	55	55	47	59	42
Trust FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes	Yes	Yes	Yes
Control for total FCEs	Yes	Yes	Yes	Yes	Yes	Yes
Control for staffing levels	Yes	No	No	No	No	No
Control for operating expenses	Yes	No	No	No	No	No
Control for AF and CDV prevalence	No	Yes	No	No	No	No
Control for all prevalence	No	Yes	No	No	No	No
Control for Hep C admission FCEs	No	No	No	Yes	No	No
Sample	All	All	All	All	Dasabuvir	Sofosbuvir

Notes: Dependent variable is the natural logarithm of prescribing Hepatitis C medicines in Columns (1)-(10) and the winsorised prescribing in Columns (11)-(12). All columns include provider, quarter and medicine fixed effects, and controls for total hospital activity. Column (2) uses one forward lead of the operating surplus/deficit and Column (3) uses the contemporaneous value of the operating surplus/deficit and two forward leads. Column (4) uses one lag of the operating surplus/deficit and Column (5) adds a two-period lag. Column (6) uses both two leads and lags along with the contemporaneous value of the operating surplus/deficit. Column (8) uses the percentage surplus/deficit relative to operating income as an independent variable instead of the standardised values. Column (9) uses an indicator variable for having a non-negative operating surplus and Column (10) interacts the standardised operating surplus/deficit with the indicator for a non-negative surplus. Columns (11) and (12) use the winsorised definition of prescribing at the 1% and at the 0.1% level. Column (13) uses additional controls for operating expenses (clinical, non-clinical, staffing, premises, drug costs and transport) as well as staffing levels. Column (14) controls for primary care prevalence at ICB boundaries for Atrial fibrillation and cardiovascular disease only and Column (15) controls for all large diseases prevalence. Column (16) restricts the sample to prescribing for admitted Hepatitis C patients as recorded by the HES statistics. Columns (17) and (18) restrict the sample to prescribing only for Dasabuvir or Sofosbuvir, respectively. Standard errors clustered at the provider level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Main results OLS with alternative clustering - Prescribing Hepatitis C medicines

Outcome:	(1) Hepatitis C prescribing	(2) Hepatitis C prescribing	(3) Hepatitis C prescribing
Std. operating surplus/deficit	0.168**	0.167**	0.152**
Baseline st. errors (provider)	(0.063)	(0.064)	(0.061)
Provider and quarter	(0.060)	(0.060)	(0.059)
ICBs	(0.063)	(0.064)	(0.056)
ICBs and quarter	(0.063)	(0.063)	(0.066)
Region	(0.065)	(0.077)	(0.062)
wild cluster bootstrap p-value	0.040	0.082	0.264
N	565	565	565
N providers	62	62	62
Trust FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes
Control for total FCEs	No	Yes	Yes
Control for operating income	No	Yes	Yes
Control for operating expenses	No	No	Yes

Notes: Dependent variable is the natural logarithm of prescribing Hepatitis C treatments. All columns include provider, quarter and medicine fixed effects and a control for the hospital activity captured by the total finished consultant episodes (FCEs). Column (2) adds a control for the operating income and Column (3) adds also the operating expenses controls. Standard errors clustered at the provider level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: IV first stage table 1/2

	(1)	(2)	(3)	(4)	(5)
Neoplasms	9.677***			7.588***	4.890*
	(3.564)			(2.883)	(2.648)
Blood, immune mechanism	-1.411			-4.042**	-3.279**
	(1.454)			(1.592)	(1.569)
Endocrine, nutritional, metabol.	-0.451			-3.334	-3.268
	(2.588)			(2.705)	(2.709)
Mental and behavioural	0.290			-3.533	-2.687
	(0.877)			(4.768)	(4.269)
Nervous system	6.301**			6.531**	4.808*
	(2.778)			(2.591)	(2.527)
Eye and adnexa	2.180			2.187	3.069**
	(1.600)			(1.773)	(1.474)
Ear and mastoid process	-1.026			-0.315	-0.404
	(0.820)			(1.043)	(0.976)
Circulatory system	-2.186			-2.455	-2.627
	(2.375)			(2.602)	(2.342)
Respiratory system	-1.572			-1.511	-3.478
	(3.622)			(3.697)	(3.180)
Digestive system	-7.850**			-4.833	-7.526**
	(3.897)			(3.871)	(3.550)
Skin and subcutaneous tissue	-4.274*			-4.046	-1.051
	(2.457)			(3.491)	(3.153)
Musculoskeletal and connective	-4.904			-3.893	-2.031
	(3.247)			(3.360)	(3.234)
Genitourinary system	1.981			3.157	3.924
	(3.333)			(3.391)	(3.020)
Pregnancy, childbirth	3.263			3.213	3.228
	(3.098)			(2.385)	(2.104)
Perinatal period conditions	6.300***			4.762***	5.407***
	(1.826)			(1.690)	(1.866)
Congenital malformations	-5.460			-7.728**	-2.179
	(3.911)			(3.859)	(3.994)
Symptoms, signs and abnormal	0.454			-0.675	-1.393
	(2.006)			(2.453)	(2.363)
Injury, poisoning	0.862			2.671	1.860
	(3.620)			(5.404)	(4.837)
Health status factors	-2.528**			0.307	3.117***

Notes: Dependent variable is the standardise operating surplus/deficit. Column (1) uses all disease groups as counts (FCEs) and as percentage of total activity. Columns (2) and (3) add two lags of the annual surplus deficit and the operating surplus/deficit, respectively. Columns (4) and (5) use the disease activity and the lags financial positions together. Standard errors clustered at the provider level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: IV first stage table 2/2

	(1)	(2)	(3)	(4)	(5)
	(1.182)			(1.237)	(1.194)
Infectious and parasitic %	-76.285			13.650	61.147*
	(49.236)			(40.542)	(35.374)
Neoplasms %	-179.634***			-64.839	29.568
	(55.426)			(46.071)	(43.870)
Blood, immune mechanism %	-19.897			277.137*	303.625**
	(142.386)			(146.431)	(141.235)
Endocrine, nutritional, metabol. %	102.497			404.642	435.809
	(260.035)			(264.109)	(268.506)
Mental and behavioural %	-29.594			615.689	570.565
	(65.599)			(609.115)	(555.870)
Nervous system %	-659.443***			-572.203***	-396.878*
	(242.170)			(218.190)	(214.826)
Eye and adnex %	-131.677**			-45.459	-6.362
	(65.137)			(56.599)	(50.668)
Ear and mastoid process %	58.044			-66.885	57.280
	(378.838)			(454.642)	(432.971)
Circulatory system %	-18.491			43.285	93.506
	(80.262)			(85.253)	(80.156)
Respiratory system %	-3.320			87.835	191.751**
	(107.839)			(103.773)	(94.679)
Digestive system %	33.413			77.563	168.646***
	(67.126)			(60.427)	(56.468)
Skin and subcutaneous tissue %	192.716			282.207	125.368
	(176.363)			(245.034)	(222.012)
Musculoskeletal and connective %	9.026			74.004	93.345
	(76.150)			(81.217)	(83.109)
Genitourinary system %	-74.390			-31.140	22.703
	(111.184)			(109.194)	(98.143)
Pregnancy, childbirth %	-179.805**			-62.163	43.657
	(81.688)			(66.972)	(62.782)
Perinatal period conditions %	-544.577***			-361.061**	-379.173**
	(181.214)			(159.635)	(182.078)
Congenital malformations %	555.183			900.570*	486.453
	(486.620)			(500.215)	(478.161)
Symptoms, signs and abnormal %	-70.395			36.301	97.232*
	(58.034)			(57.464)	(56.031)
Injury, poisoning %	-90.564			-42.101	62.409
	(84.456)			(133.246)	(127.450)
(t-1) Std. annual surplus/deficit		0.269***	0.652***	0.001	1.026***
		(0.101)	(0.107)	(0.137)	(0.268)
(t-2) Std. annual surplus/deficit		-0.033	0.329*	-0.092	0.275**
		(0.088)	(0.199)	(0.104)	(0.115)
(t-1) Std. operating surplus/deficit			-0.482***		-0.813***
			(0.103)		(0.198)
(t-2) Std. operating surplus/deficit			-0.443*		-0.438***
			(0.237)		(0.136)
N	517	527	527	476	476
Trust FE	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes	Yes	Yes
Control for total FCEs	Yes	Yes	Yes	Yes	Yes
Control for operating income	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable is the standardise operating surplus/deficit. Column (1) uses all disease groups as counts (FCEs) and as percentage of total activity. Columns (2) and (3) add two lags of the annual surplus deficit and the operating surplus/deficit, respectively. Columns (4) and (5) use the disease activity and the lags financial positions together. Standard errors clustered at the provider level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A9: Prevalence exogeneity of large disease groups in primary care

Outcome:	(1) Hepatitis C referrals	(2) Hepatitis C referrals	(3) Hepatitis C referrals	(4) Hepatitis C referrals	(5) Hepatitis C referrals	(6) Hepatitis C referrals
Atrial fibrillation	0.196***	0.198***			0.188***	0.194***
	(0.055)	(0.056)			(0.055)	(0.055)
Coronary heart disease	-0.086	-0.078			-0.087	-0.077
	(0.068)	(0.069)			(0.069)	(0.069)
Cardiovascular disease†	0.029**	0.027**			0.028**	0.026**
	(0.013)	(0.013)			(0.013)	(0.013)
Heart failure	0.029	0.010			0.028	0.011
	(0.043)	(0.043)			(0.043)	(0.043)
Left ventricular systolic dysfunction	0.004	-0.017			0.003	-0.015
	(0.039)	(0.040)			(0.039)	(0.040)
Hypertension	-0.044	-0.042			-0.050	-0.044
	(0.046)	(0.054)			(0.059)	(0.061)
Peripheral arterial disease	-0.055	-0.068			-0.056	-0.068
	(0.052)	(0.053)			(0.052)	(0.053)
Stroke and transient ischaemic attack	0.014	0.008			0.009	0.007
	(0.065)	(0.066)			(0.066)	(0.067)
Cancer			0.085*	0.052	0.058	0.034
			(0.044)	(0.045)	(0.044)	(0.045)
Chronic kidney disease‡			-0.026	-0.035*	-0.027	-0.033
			(0.020)	(0.020)	(0.020)	(0.021)
Diabetes mellitus			-0.016	-0.006	0.002	0.016
			(0.039)	(0.057)	(0.063)	(0.069)
Palliative care			0.013	0.011	0.009	0.009
			(0.021)	(0.021)	(0.021)	(0.021)
N	20,328	20,328	20,328	20,328	20,328	20,328
GP FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls: total GP patients	Yes	Yes	Yes	Yes	Yes	Yes
Controls: other prevalence and demographics	No	Yes	No	Yes	No	Yes

Notes: Dependent variable is the natural logarithm of Hepatitis C prevalence and covariates of interest are the logged prevalence levels in the cardiovascular diseases (CVD) and the high dependency diseases (HDD). All columns include GP and year fixed effects and a control for the size of the GP practice (all registered patients). Columns (2), (4) and (6) include additional controls: i) demographic profiles of patients: percentage male and female of age groups in ten year intervals and ii) other diseases prevalence (asthma, chronic obstructive pulmonary disease, obesity, dementia, depression, epilepsy, mental health, osteoporosis and rheumatoid arthritis). † "Cardiovascular disease (primary prevention ages 30 - 74)", ‡ "Chronic kidney disease prevalence (ages 18+)". Standard errors clustered at the GP level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Mediation: drug costs and mortality indicator

Outcome:	(1) Drug costs	(2) SHMI score	(3) SMHI banding	(4) Hepatitis C prescribing	(5) Hepatitis C prescribing	(6) Hepatitis C prescribing
Std. operating surplus/deficit	-0.011**	0.179***	0.173**	0.175***	0.183***	0.178***
	(0.005)	(0.064)	(0.068)	(0.059)	(0.057)	(0.058)
SMHI value		-1.623			-1.905	
		(1.232)			(1.771)	
SMHI banding			-0.055			0.008
			(0.168)			(0.229)
Drug costs				0.467		
				(1.275)		
ACME				-0.004	-0.005	-0.001
Direct Effect				0.171	0.177	0.176
Total Effect				0.175	0.183	0.177
N	566	555	555	565	555	555
Trust FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Medicine FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is the potential mediator in columns (1)-(3) and Hepatitis C prescribing in Columns (4)-(6). Drug costs and prescribing are logged. Higher values of the Summary Hospital-level Mortality Indicator (SHMI) mean worse mortality. The table reports also the average causal mediation effect (ACME) from the mediation analysis along with the total and direct effects. Standard errors clustered at the provider level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

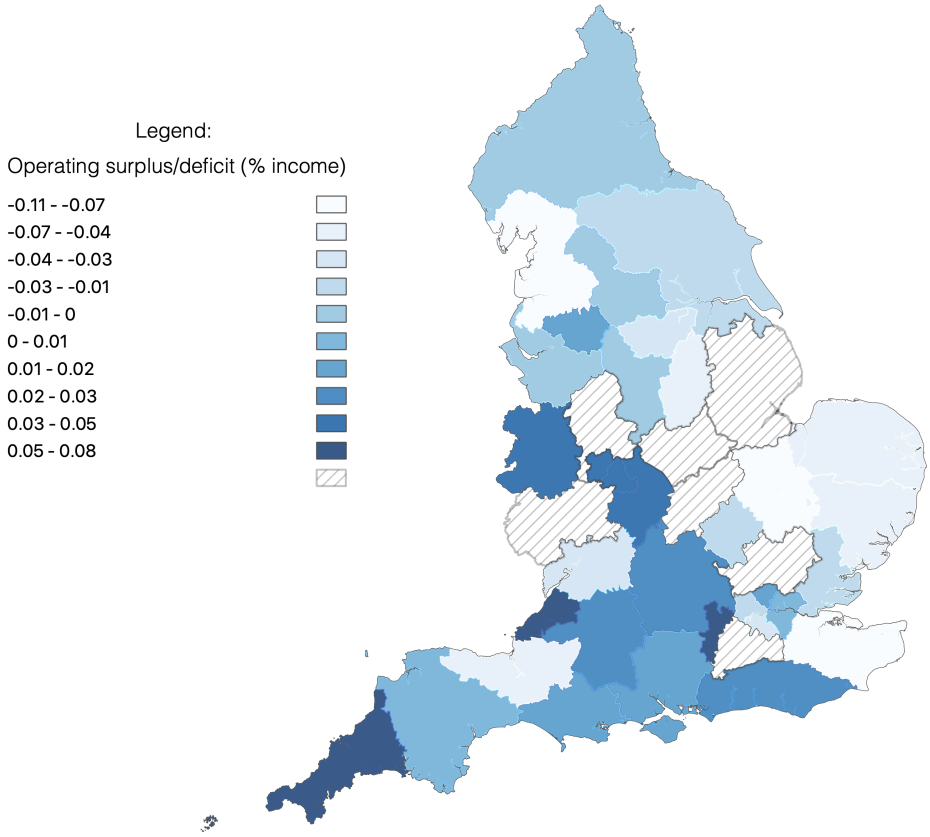
Table A11: Mediation: staffing levels

Panel A – Outcome:	(1) Medical and dental	(2) Admin and estates	(3) Health assistance and support	(4) Nurses, midwives and health visitors	(5) Scientific, therapeutic and technical	(6) Health science Health
Std. operating surplus/deficit	0.117	0.213	-0.258	0.062	-0.047	-0.090*
	(0.246)	(0.138)	(0.328)	(0.134)	(0.080)	(0.052)
N	565	565	565	565	565	565
Trust FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Panel B – Outcome:	(1) Hepatitis C prescribing	(2) Hepatitis C prescribing	(3) Hepatitis C prescribing	(4) Hepatitis C prescribing	(5) Hepatitis C prescribing	(6) Hepatitis C prescribing
Std. operating surplus/deficit	0.179***	0.191***	0.186***	0.186***	0.181***	0.186***
	(0.057)	(0.057)	(0.058)	(0.057)	(0.057)	(0.058)
Nurses, midwives, health visitors	0.003					
	(0.023)					
Admin and estates		-0.042				
		(0.030)				
Health assistance and support			0.010			
			(0.014)			
Scientific, therapeutic and technic				-0.035		
				(0.036)		
Medical and dental staff					0.027	
					(0.073)	
Health care science						0.049
						(0.080)
ACME	0.002	-0.011	-0.007	-0.006	-0.001	-0.006
Direct Effect	0.181	0.181	0.180	0.181	0.180	0.180
Total Effect	0.179	0.192	0.187	0.187	0.182	0.186
N	565	565	565	565	565	565
Trust FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variable is proportion in the six main staff groups in Panel A and the natural logarithm of Hepatitis C prescribing in Panel B. The table reports also the average causal mediation effect (ACME) from the mediation analysis along with the total and direct effects. Standard errors clustered at the provider level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

B Appendix Figures

Figure B1: Map of surplus/deficit as percentage of operating income.



Notes: The map shows the average surplus/deficit as percentage of operating income within the ICB boundaries within ten equal quantiles, average over the 2015-2018 period.

Figure B2: Density of operating surplus or deficit, winsorised fraction 0.01

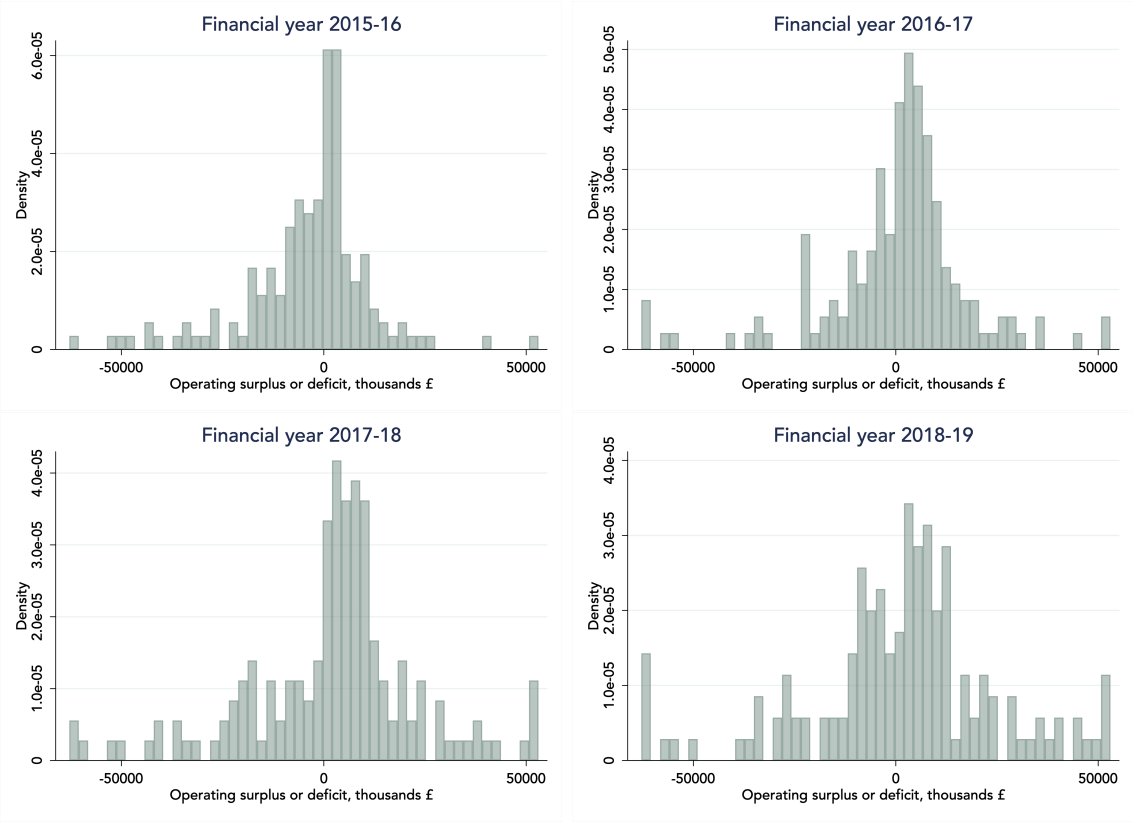
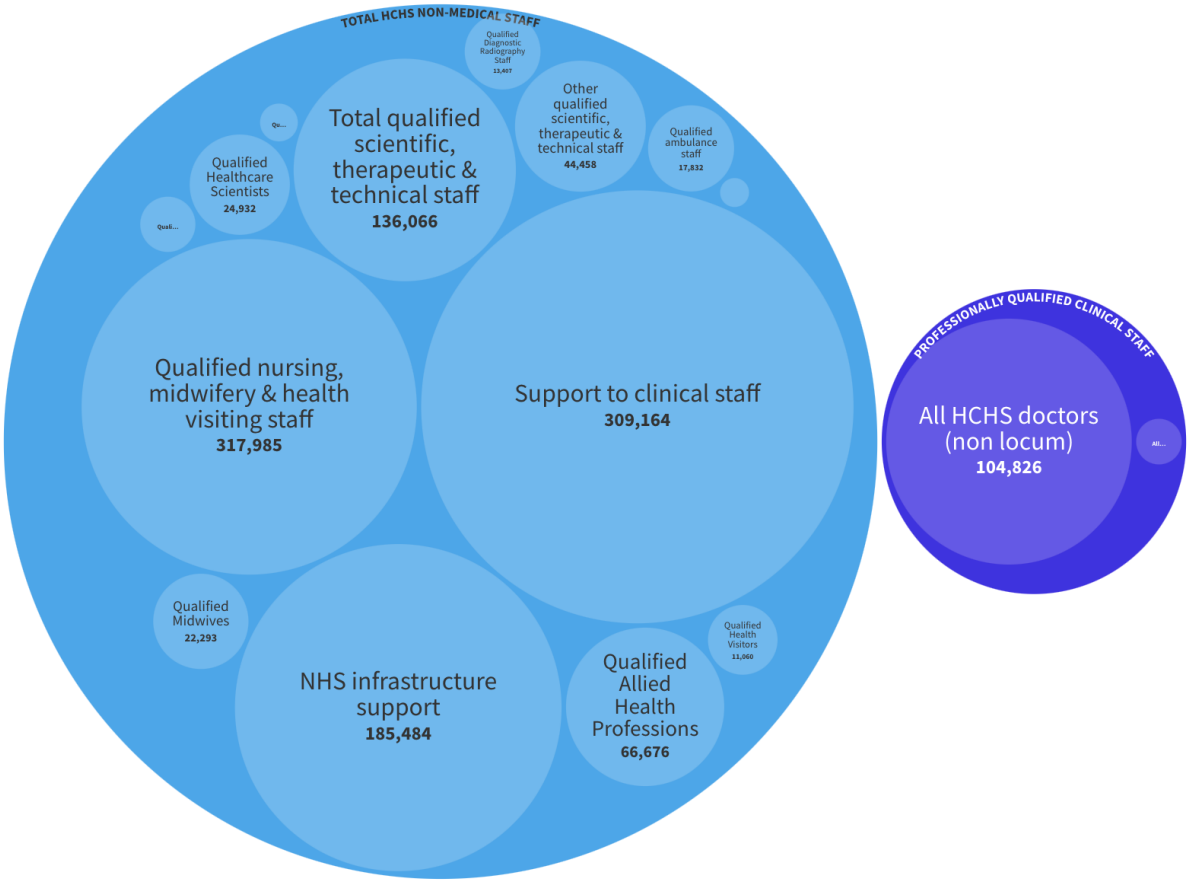
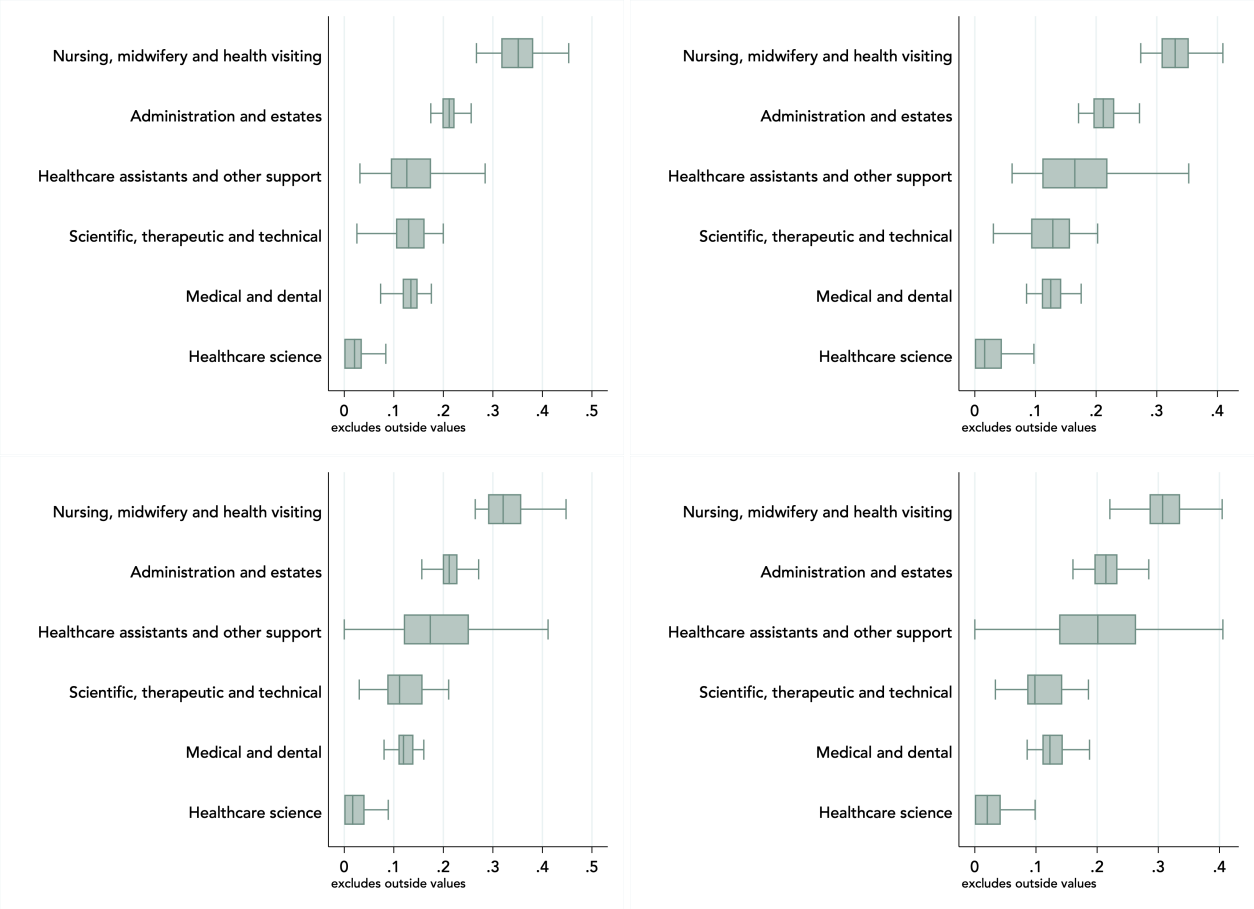


Figure B3: NHS Hospital & Community Health Service (HCHS) monthly workforce statistics - January 2015



Notes: Full Time Equivalent (FTE) refers to the proportion of each role's full time contracted hours that the post holder is contracted to work. 1 would indicate they work a full set of hours, 0.5 that they worked half time. Full Time Equivalent (FTE) refers to the proportion of each role's full time contracted hours that the post holder is contracted to work. 1 would indicate they work a full set of hours, 0.5 that they worked half time. Dynamic circles hierarchy at: https://public.flourish.studio/visualisation/14929594/

Figure B4: Percentage of total staff, average 2015-2018



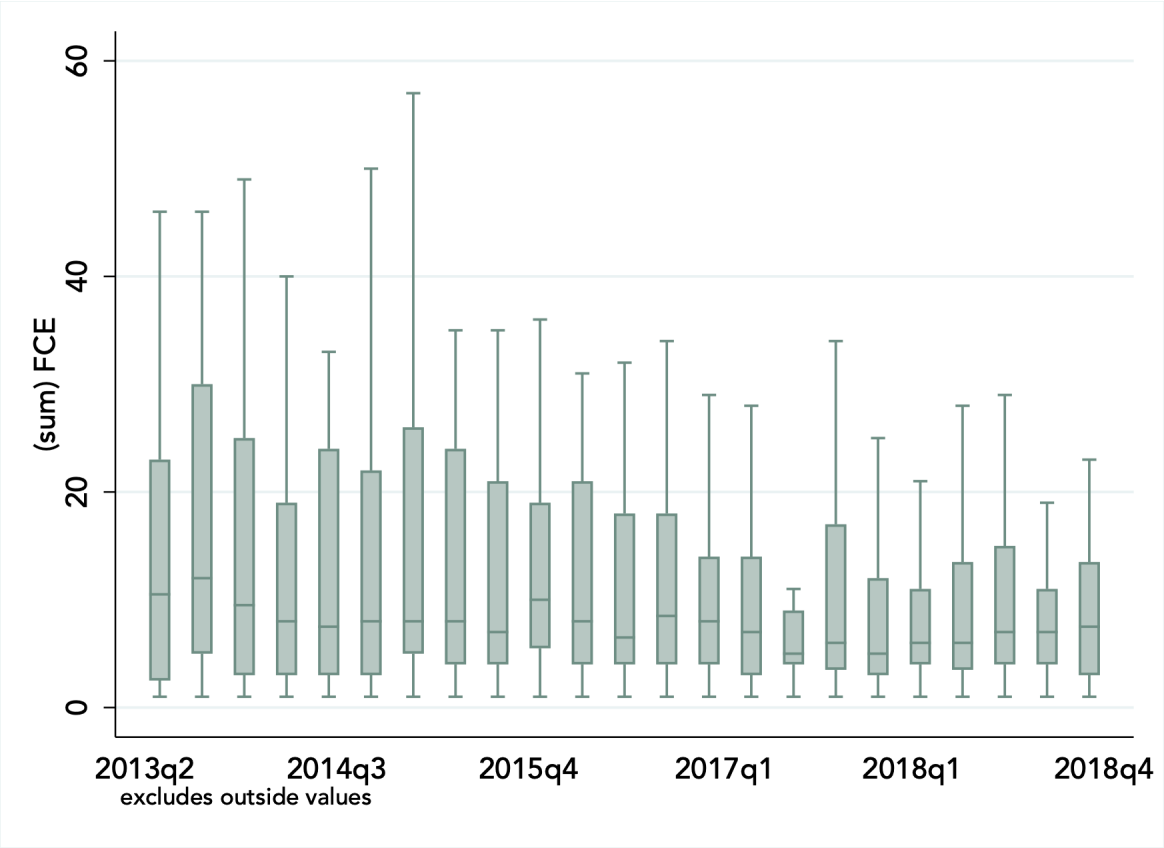


Figure B5: Number of Hepatitis C FCE episodes per provider per quarter

Figure B6: Prevalence of cardiovascular diseases I: Atrial fibrillation, Coronary heart disease, Cardiovascular disease, and Heart failure

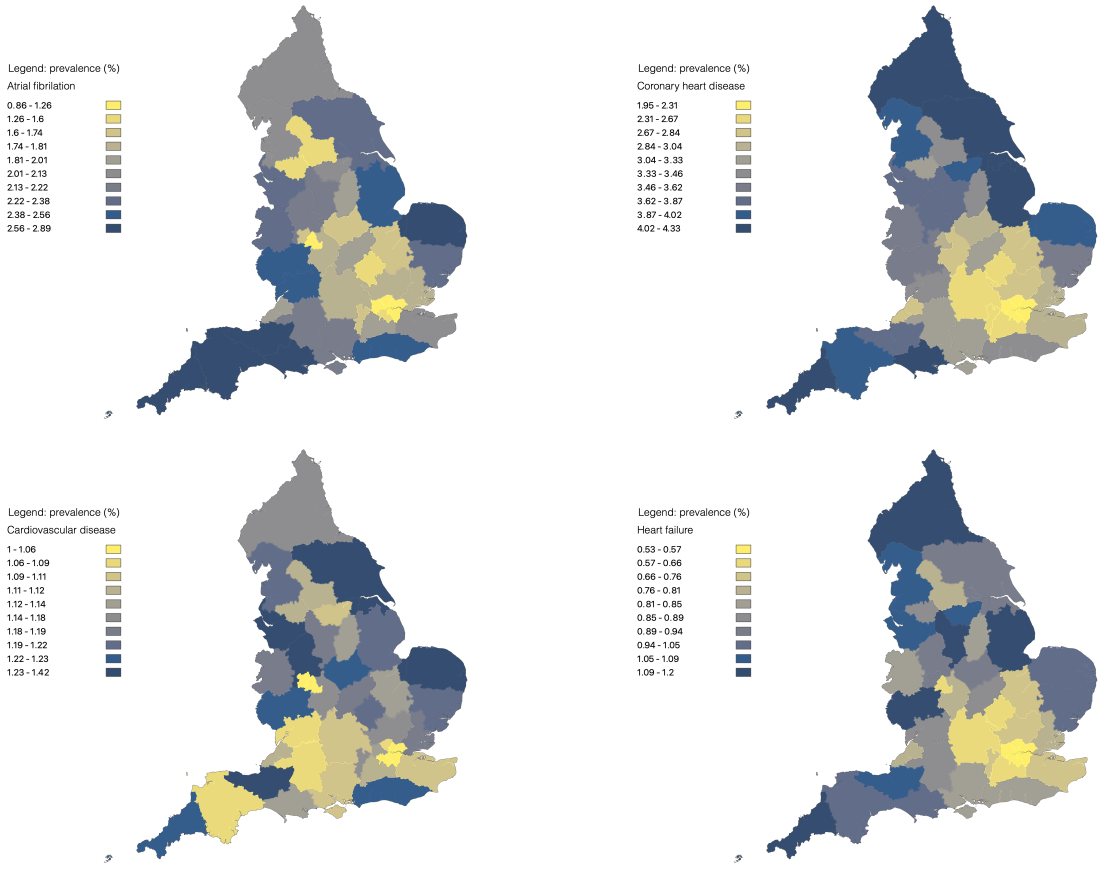


Figure B7: Prevalence of cardiovascular diseases II: Left ventricular systolic dysfunction, Hypertension, Peripheral arterial disease, and Stroke & transient ischaemic attack

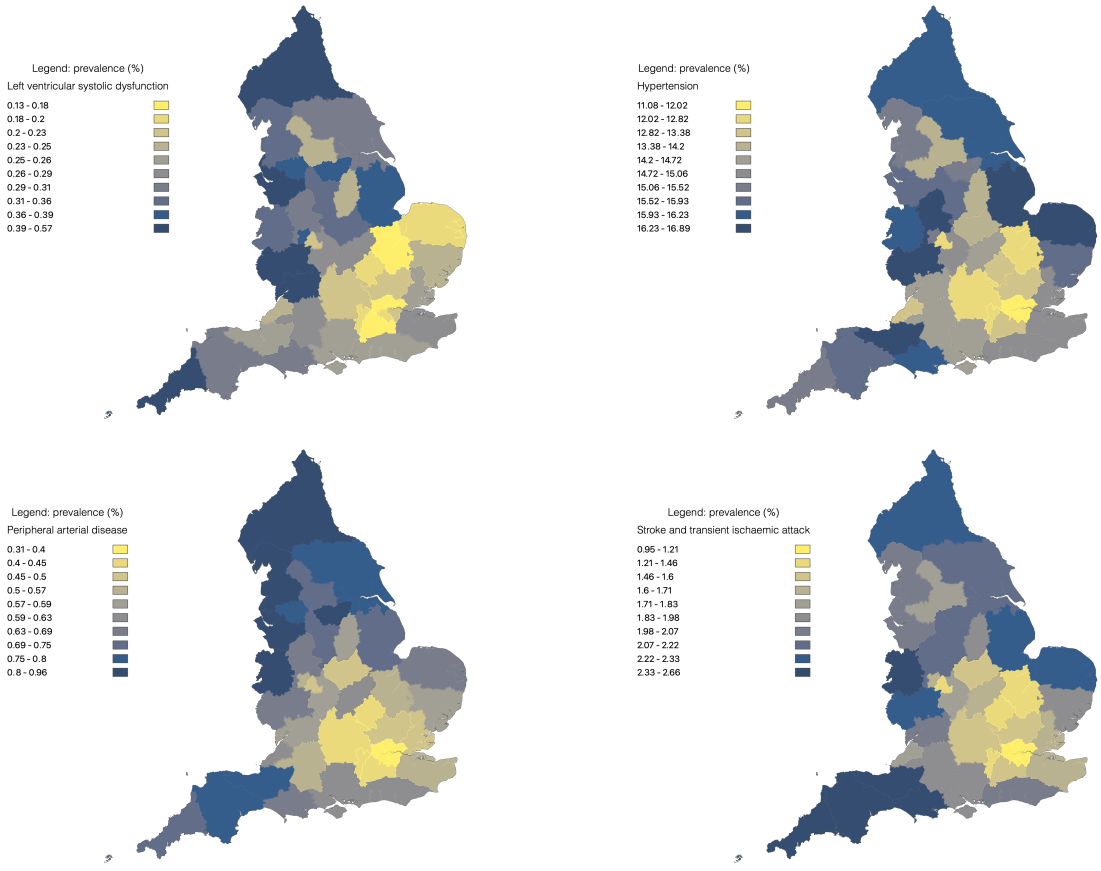


Figure B8: Prevalence of high dependency diseases: Cancer, Chronic kidney disease, Diabetes mellitus and Palliative care