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Static regulation and technological change: Prescribing cost-effective treatments under financial constraints in the English NHS

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Static regulation and technological change: Prescribing cost-effective treatments under financial constraints in the English NHS*

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Abstract

Despite the long-term benefits of new health technologies, their optimal adoption may be impeded by the financial constraints of a public health system. In this paper we assess whether financially constrained hospital trusts ration cost-effective but expensive innovative treatments. Given financial pressures, exogenous to small disease populations, accumulated debt may prevent optimal prescribing. In such circumstances, financially constrained hospital trusts may choose to ration the use of these treatments in the short-term, even though their prescribing may be a more efficient use of funds in the long-term. We consider two small disease populations of particular interest where recent innovative medicines have become available: hepatitis C and multiple sclerosis. Combining and analysing a novel panel dataset of 150 hospital trusts providing acute care in the United Kingdom, we find evidence of rationing new cost-effective treatments under financial constraints.

Keywords: healthcare budgets, cost-effectiveness, prescribing
JEL Codes: I18, I11, H51

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1 Introduction

Despite the long-term benefits of some new medicines, when the health systems employ static decision rules, healthcare service providers may not make optimal decisions. In particular, when the benefits are very large in magnitude, e.g. when the long-term incidence is estimated to decline significantly, medicines are priced at a substantially higher rate to account for the reduction in the patient population over time. This higher prices may not be affordable in the short-term if providers are required to meet set budgets.

The English National Health Service (NHS) spent almost £21 billion on drugs in 2019/20, where hospital use accounted for 56% of the total cost at list price in 2019/20.[1] There is an argument that technological change is a key driver of increasing costs within health systems. (Sorenson et al., 2013; de Meijer et al., 2013; Santana et al., 2020). Technology adoption has, alongside other factors, increased population longevity but with poorer average health outcomes for the elderly. Some disease groups like heart disease, cancer, stroke, diabetes exert disproportionate burden on health systems and their budgets (Lim et al., 2012; Murray and Lopez, 2013). This has resulted in health authorities introducing various cost-containment measures such as spending caps on medicines to limit these costs.

In this paper, we consider whether there is sub-optimal prescribing of cost-effective treatments that generate health returns in the longer-term in a setting where hospitals face constraints under 'static' or non-adaptive regulatory frameworks. These institutional frameworks and policies are not able to account for the dynamic health benefits of new treatments. This is not to say that all new treatments generate wide-ranging benefits, however, in our paper we focus on cases where these longer-term health benefits are well-established. We focus our investigation on secondary care providers known as 'trusts' in the English National Health Service (NHS). We consider whether financially constrained trusts are less likely to prescribe these new therapies despite their long-term benefits.

We study small patient population diseases, namely Hepatitis C (Hep C) and Multiple

[1] Prescribing Costs in Hospitals and the Community 2019-2020

Sclerosis (MS) that are not likely to have an impact on trust finances directly but also have new cost-effective treatments available during the period under consideration. Particularly, when new therapies generate large benefits, for example to reduce long-term incidence of a small population communicable disease like Hep C, then prices for these treatments take into account the dynamic benefits that these therapies generate in future. These higher prices may not be affordable in the short-term if providers are required to meet set budgets and targets.

To estimate how prescribing for smaller disease groups is impacted by the accumulated deficits of healthcare providers, we use an identification strategy of panel fixed effects. Our analysis proceeds in two steps. First, we show how the variation in prescribing is predicted by contemporaneous and lagged values of the trusts' surplus/deficit. Second, we show that the prevalence of the small disease groups is not explained by the large disease groups: the high dependency diseases (HDD) and cardiovascular diseases (CVD), which are known to exert significant pressure on the healthcare budgets.

Our main results indicate that a 10% standard deviations increase in the trust's surplus (about £2 million) is correlated with 5.6% increase in prescribing of the new medicines. These results are driven by the Hep C prescribing, where this effect has a larger magnitude: a 10% st. dev. increase in the trust's surplus is correlated with 17.6% increase in prescribing of the Hep C medications. Our work provides evidence for the need for more dynamic regulatory frameworks that take into account the dynamic benefits of technology adoption.

Our paper contributes to the literature on optimal budget decisions under financial constraints (Anderson et al., 2012). It is also relevant to the study of financial incentives and fiscal externalities (Finkelstein, 2004; Lin and Sacks, 2019; Starc and Town, 2020). Our analysis also speaks to the question of how to design well-functioning, fair and optimal funding schemes in health care where (Burau et al., 2018; Lundkvist, 2002; Schmitz, 2013; Duggan, 2005).

The rest of this paper is organised as follows. First, section 2 describes the institutional

context, setting out in more detail the regulatory and policy environment facing trusts in the English NHS. Then, section 3 describes the data sources in this investigation alongside key summary statistics and section 4 sets our empirical strategy. Section 5 presents the key results and 6 sets out a brief of their implications and finally, section 6 provides some discussion and sets out concluding remarks.

2 Institutional context and background

2.1 Payments to Hospital Trusts

Trusts are the main provider of tertiary and secondary care and they budgets are allocated based on the national allocation from central government and previous budgets. Payments are largely made on the basis of activity. The national tariff sets out prices and rules for determining prices payable by NHS commissioners to hospitals for providing NHS-funded healthcare. It was introduced as part of a package of reforms including allowing patients to choose which hospital they are treated, and the tariff enabled the money to follow the patient. Alongside this, it also means that all providers of NHS-funded services receive the same amount of money per operation or appointment, ensuring providers compete on quality, although there is a provision to set local prices if the national tariff is not appropriate.

In secondary care, currently there are two type of providers NHS Trusts and NHS Foundation Trusts. NHS trusts are public sector bodies established by parliamentary order by the secretary of state for health to provide healthcare services to the NHS. All NHS trusts are expected to become foundation trusts in due course.

Foundation trusts are semi-autonomous and have some managerial and financial freedom when compared NHS Trusts. Foundation trusts were introduced in 2002 as part of legislation to create a 'patient-led' internal market within the NHS. By April 2020 there were 151 Foundation Trusts overall, and 76 NHS Trusts excluding Foundation Trusts.

2.2 NICE and MHRA

The overall framework and clinical guidelines for innovative new drugs is developed by the National Institute of Care and Excellence (NICE) and the Medicines and Healthcare products Regulatory Agency (MHRA). NICE evaluates the cost-effectiveness of new medicines and recommends those which it believes offer good value for money for use in the NHS. MHRA evaluates the efficacy and safety of medicines before these medicines are given market authorisation for sale in the UK.

When a new medicine becomes available, it's cost-effectiveness is evaluated by NICE and if it offers 1 unit of standardised health, a Qualtiy Adjusted Life-Year (QALY), per £30,000 spent, then it is deemed cost-effective. The treatments recommended by NICE in its technology appraisal programmes must be funded by the NHS, by law, through what's called the 'funding directive'. However, whether a treatment is prescribed largely depends on the prescriber.

NICE requires hospital trusts to make funding available for treatments it recommends for use, but hospital trusts are also penalised for running significant deficits.

2.3 Hepatitis C and Multiple Sclerosis (MS)

Hepatitis C is an infectious disease that can affect the liver. It is spread through spread blood-to-blood contact and there is no vaccine that can prevent its transmission. In the UK, most Hepatitis C infections happen in people who inject drugs or have injected them in the past (can be also transmitted through sharing razors and toothbrushes).[2] Using the latest medications, more than 90% of people with hepatitis C may be cured, yet access to the latest treatments is still limited. [3]

Multiple sclerosis is a lifelong condition, affecting the brain and spinal cord that can sometimes cause serious disability, yet it can occasionally be mild. It is an autoimmune

[2]NHS overview on Hepatitis C
[3]Hepatitis C key facts by the WHO

condition, that is when something compromises the immune system and it mistakenly attacks a healthy part of the body. While there is currently no cure for MS, there are a number of treatments can help control the condition and ease symptoms.[4]

2.4 Innovative treatments

New treatments are recommended by NICE based on the treatments national reference price. However, trusts group together regionally to purchase drugs from suppliers. This price can vary from between trusts based on different procurement strategies.

Two cost-effective treatments can vary significantly in cost as well. For example, a 12-week course for chronic Hepatitis C (Hep C) medicine based on the latest treatments available costs approximately to £36,000[5] while a the cost for Multiple Sclerosis (MS) patients is approximately £14,000 per year.[6] However, in the case of Hep C the treatment is virtually a cure and therefore generates significantly more health benefits for the patient population it treats.

Since Hep C is a communicable disease, reducing prevalence of the disease generates even greater benefits in the longer-term as it reduces the patient population. The treatments for MS on the other hand do not generate as many health benefits for the patient population they treats and patients can be on the treatments for several years. The size the patient populations for chronic Hep C and MS are similar, with there being an estimated 81,000 patients with chronic Hep C in England[7] and 105,000 patients with MS in England[8].

[4]NHS overview on Multiple sclerosis (MS).
[5]NICE: More options to be made available to treat hepatitis C, 2016
[6]NICE: Teriflunomide for treating relapsing–remitting multiple sclerosis
[7]UK Health Security Agency, Hepatitis C in England 2022
[8]Public Health England, Multiple sclerosis: prevalence, incidence and smoking status - data briefing

3 Data

We combine data from several sources to investigate the impact of financial indebtedness on prescribing in small disease groups. First, we use financial information from annual reports from the Foundation Trust Consolidation (FTC) accounts published by NHS England.[9] Second, as we primarily focus on secondary care, we use published statistics on hospital purchase data for innovative medicines from NHS Digital.[10] Finally, for consultant episodes for various diseases, we use data from Hospital Episode Statistics (HES) published monthly activity data, published by NHS Digital.[11]

We extract the operating surplus/deficit, the surplus/deficit for the year (resulting from adding the net finance costs) and the total comprehensive income/expense for the period (adding impairments, revaluations, other gains and losses, reserve movements, etc.). To remain agnostic about accounting particularities, we use operating surplus/deficit for our analysis, as it nets operating income from patient care activities, other operating income and operating expenses.

The summary statistics are reported in Table 1, where Panel A describes the financial panel information available in our dataset during the 2009/10 to 2019/20 period for about 150 NHS foundation trusts. The average surplus per trust is 1,958,000 pounds per trust, with substantive variation across regions and time. The lower part of Panel A tabulates the summary statistics by region where it is evident that some regions like the East of England, London and North East Yorkshire have an average operating deficit over this time period, whereas all other regions have an operating surplus. Figure 1 shows the between variation, expressed as the density of the annual operating surplus/deficit. For instance, the financial years 2011/12, 2016/17 and 2017/18 have more pronounced surplus with a bulk of the distribution on the positive side. For our analysis we use standardised values of the variable operating surplus/deficit.

[9]NHS England trust accounts consolidation (TAC) data publication
[10]NICE Technology Appraisals in the NHS in England
[11]NHS Digital Monthly Hospital Activity Data

Panel B of Table 1 summarises the prescribing variables in our panel dataset. The value we use is constructed by ratio between a numerator, which measures supplies of medicines recorded in the hospital pharmacy departments in the unit of the treatment e.g. mgs and the denominator, measured in Finished Consultant Episodes (FCEs) days 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 study two high-level conditions, Hepatitis C and Multiple Sclerosis. All treatments included have been recommended for use in the NHS by NICE and have been deemed cost-effective. Table 2 sets out the treatments included for each high-level condition and their date of approval by NICE.

4 Empirical strategy

To estimate how smaller disease groups are impacted by the accumulated deficits of health-care providers, we use an identification strategy of panel fixed effects. Our analysis proceeds in two steps. First, we show how the variation in prescribing is predicted by contemporaneous and lagged values of the trusts' surplus/deficit. Second, we show that the prevalence of the small disease groups is not explained by the large disease groups: the high dependency diseases (HDD) and cardiovascular disease (CVD), which are known to exert significant pressure on the healthcare budgets.

4.1 Prescribing and NHS trust deficits

In Equation 1, we explain the variation in the levels of prescribing by the operating surplus/deficit of the healthcare provider, accounting for a number of possible unit-specific and time-specific heterogeneities. We use condition fixed effects (differentiating between Hepatitis C and Multiple Sclerosis) and treatment fixed effects, where e.g. different therapy levels would require different dosages.

We apply provider fixed effects, which would capture time-invariant trust-specific unobserved heterogeneities, including e.g. regional variations in healthcare need and levels of multiple deprivation, financial management, staffing and others. We also apply time fixed effects to account for common shocks to all trusts including seasonality and other macro conditions affecting all providers simultaneously.

Our key identification assumption is that the static rules about budget allocation are not accounting for the benefits of prescribing the medicine as soon as it becomes available. Incidence of Hep C and MS does not affect budget deficits, which is driven by incidence of other larger disease groups (e.g. cancer, cardiovascular disease).

$$log(Prescribing)_{ijqt} = \sum_{k=0}^{3} \beta_{d,t-\tau} \cdot std(SurplusDeficit)_{it-\tau} + \alpha_i + \delta_q + \theta_j + \epsilon_{ijqt} \quad (1)$$

i denotes an NHS trust, q denotes the quarter and j the therapy. The dependent variable incorporates the prescribing of new medicines – value per quarter q – within a particular therapy j, within a small disease condition. The prescribing value is generated by a numerator, capturing the quantity prescribed, divided a numerator, which is the measure of activity for that hospital within that quarter.

The independent variable of interest is the standardised value of the Surplus/Deficit observed for a provider i in year t. We lag the Surplus/Deficit variable up to 2 periods in our main specification, to account for the cumulative effect of indebtedness. This is the treatment variable and we note that it has lower time frequency t than the prescribing data which is available at the quarterly level qt. α_i represents trust fixed effects, δ_t are time fixed effects and θ_j are therapy fixed effects. Further we split the sample by condition – hepatitis C or multiple sclerosis – and present our preferred final specification separately for both disease groups.

4.2 Exogeneity: Prevalence of small and large disease populations

In Equation 2, we investigate in turn whether whether small disease activity levels, measured by consultant episodes for multiple sclerosis and hepatitis C are not correlated with the high secondary care utilisation disease prevalence and activity. To conduct this analysis we look at the primary care setting.

This empirical specification is intended to test the exogeneity of the small disease prevalence and the activity within larger disease groups, which are known to impact the healthcare budgets disproportionately. If there were a relationship between small and large diseases prevalence, then the exogeneity of the budget deficits in Equation 1 is not credible.

$$Prevalence^{k}_{gt} = \beta_{hdd} \cdot Prevalence^{HDD}_{gt} + \beta_{cvd} \cdot Prevalence^{CVD}_{gt} + \alpha_g + \delta_t + \epsilon_{gt} \qquad (2)$$

g denotes a GP practice and t denotes a year. The dependent variable $Prevalence^{k}_{gt}$ are the full consultant episodes (FCE) of condition k, namely MS and Hep C per GP, per year. Then we use a range of covariates including activity in the large disease groups: namely prevalence of high dependency diseases (HDD) and cardiovascular disease (CVD). In essence, we would like to test whether practices with more e.g. cardiovascular and diabetes patients also have more e.g. Hep C patients or whether these activity levels are unrelated. We similarly apply GP fixed effects α_g and year fixed effects δ_t.

4.3 Explaining budgets deficits

[Work in progress] The prevalence of large disease groups – namely prevalence of high dependency diseases (HDD) and cardiovascular disease (CVD) – are known to exert disproportionate impact on budgets. Having demonstrated the plausible exogeneity of the large disease groups relative to the small disease groups in Equation 2, our next step is using an activity measure for large diseases to instrument for the surplus/deficit of NHS trusts.

This would enable us to estimate Equation 1 with instrumenting the potentially endogenous deficit variable.

In the first stage, would would show that trust budget deficits are generated by higher activity in the large disease groups. We use the following specification:

$$std(DeficitSurplus)_{it} = \beta_a \cdot Activity_{it}^{CVD,HDD} + \beta_p \cdot Prevalence_{it}^{CVD,HDD} + \alpha_i + \delta_t + u_{it} \quad (3)$$

Where $std(DeficitSurplus)_{it}$ is our potentially endogenous independent variable, measured at the trust i, year t level. The activity per trust is aggregated from the CCG to trust, where several CCG may send patients to one or more hospitals. We apply trust fixed effects i and time fixed effects t. We expect that consistently higher levels of activity in the large disease groups accumulates in higher levels of deficit.

5 Results

5.1 Prescribing

5.1.1 Main results

In Table 3 we present the main results of estimating Equation 1, where the dependent variable is the log of the prescribing value. In columns (1)-(2), we initially use OLS only gradually adding the lags of the independent variable of interest: the standardised surplus/deficit of the NHS trust. The initial OLS coefficient on β_{d0}, the contemporaneous term is positive and significant at 1%. Notable is the addition of the lags, which doubles the magnitude of the effect. As the OLS coefficient is possibly biased, we proceed with introducing a full set of fixed effect.

Column (3) presents the estimation result under the full fixed effects specification without lags. The effect of the operating surplus/deficit is positive and marginally significant. After

the addition of the lags in column (4), the coefficient nearly doubles in magnitude and becomes significant at %. This is our preferred specification when considering both conditions together. A 10% standard deviations increase in the trust's surplus (about £2 million) is correlated with 5.6% increase in prescribing of the new medicines.

We restrict the sample to only hepatitis C medicines prescribing or only multiple sclerosis prescribing in columns (5) and (6), respectively. The effect we observe is clearly driven by the hepatitis C group, where the magnitude is even larger. A 10% st. dev. increase in the trust's surplus is correlated with 17.6% increase in prescribing of the new medicines. While the sample is substantially smaller, this effect may be explained by the Hep C medicines being significantly more expensive. The surplus/deficit is not a significant predictor of multiple sclerosis prescribing.

5.1.2 Robustness

In Table 4, we present some alternative specifications for Equation 1, where we subset the sample to only Hep C prescribing. Column (1) is a specification without any lagged surplus/deficit. Then columns (2) and (3) introduce 3 and 5 lags, respectively. Due to the length of our panel, we are not able to consider a higher number of lags. The results remain robust and similar to our baseline specification. Column (4) introduces two-way clustering by quarter and provider and our results remain qualitatively similar.

5.2 Exogeneity

We consider prevalence data at the primary care level for two disease clusters that have high secondary care utilisation and investigate whether they have any correlation with FCEs for Hep C and MS, as set out in 2. Table 5 sets out the summary data for the prevalence variables and FCE data.

In Table 6 we show that hospital activity related to Hep C and MS patients is uncorrelated with the prevalence of these two high secondary care utilisation disease groups. These are

Cardio-Vascular Diseases (CVD) and High Dependency Diseases (HDD) that are primarily treated in secondary care. Column (1) estimates a fixed effects regression for FCEs for MS and columns (2) estimates a fixed effects regression for FCEs for Hep C. None of the estimated coefficients are significant for MS or Hep C.

6 Conclusion and discussion

In this paper, we considered whether hospitals facing constraints under non-adaptive regulatory frameworks on funding prescribe of approved cost-effective treatments that generate health returns in the longer-term. We combined financial accounts information on about 150 trusts in the English NHS with prescribing data in the secondary care setting. We established that higher budget surplus is correlated with higher levels of prescribing of new Hep C medicines. We also examined disease prevalence in the primary care and showed that higher disease prevalence of large disease groups does not correlate with the small disease prevalence.

Our research establishes a link between prescribing expensive but cost-effective treatments and financial constraints faced by hospitals. In particular, when a treatment reduces the long-term burden of a disease on a health system, policy and regulation needs to be able to account for these benefits to optimise health spending. Further research is needed to establish whether rationing of specific cost-effective treatments is sub-optimal or not. There is also further work needed to consider how payment systems to hospitals incentivise or disincentivise different treatments and how activity payments to hospitals in the English NHS interact with financial constraints.

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. 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). Even when evaluated as cost-effective – as is the case for the medicines we investigate – some innovative medicines may not be prescribed. 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.

References

Anderson, S. T., R. Laxminarayan, and S. W. Salant (2012). Diversify or focus? spending to combat infectious diseases when budgets are tight. *Journal of Health Economics 31*(4), 658–675.

Burau, V., H. M. Dahl, L. G. Jensen, and S. Lou (2018). Beyond activity based funding. an experiment in denmark. *Health Policy 122*(7), 714–721.

de Meijer, C., O. O'Donnell, M. Koopmanschap, and E. Van Doorslaer (2013). Health expenditure growth: looking beyond the average through decomposition of the full distribution. *Journal of health economics 32*(1), 88–105.

Duggan, M. (2005). Do new prescription drugs pay for themselves?: The case of second-generation antipsychotics. *Journal of health Economics 24*(1), 1–31.

Finkelstein, A. (2004). Static and dynamic effects of health policy: Evidence from the vaccine industry. *The Quarterly Journal of Economics 119*(2), 527–564.

Lim, S. S., T. Vos, A. D. Flaxman, G. Danaei, K. Shibuya, H. Adair-Rohani, M. A. AlMazroa, M. Amann, H. R. Anderson, K. G. Andrews, et al. (2012). A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990–2010: a systematic analysis for the global burden of disease study 2010. *The lancet 380*(9859), 2224–2260.

Lin, H. and D. W. Sacks (2019). Intertemporal substitution in health care demand: Evidence from the rand health insurance experiment. *Journal of Public Economics 175*, 29–43.

Lundkvist, J. (2002). Pricing and reimbursement of drugs in sweden. *The European Journal of Health Economics 3*(1), 66–70.

Martin, S., N. Rice, and P. C. Smith (2008). Does health care spending improve health outcomes? evidence from english programme budgeting data. *Journal of health economics 27*(4), 826–842.

Murray, C. J. and A. D. Lopez (2013). Measuring the global burden of disease. *New England Journal of Medicine 369*(5), 448–457.

Santana, I. R., M. J. Aragón, N. Rice, and A. R. Mason (2020). Trends in and drivers of healthcare expenditure in the english nhs: a retrospective analysis. *Health Economics Review 10*(1), 1–11.

Schmitz, H. (2013). Practice budgets and the patient mix of physicians–the effect of a remuneration system reform on health care utilisation. *Journal of Health Economics 32*(6), 1240–1249.

Sorenson, C., M. Drummond, and B. B. Khan (2013). Medical technology as a key driver of rising health expenditure: disentangling the relationship. *ClinicoEconomics and outcomes research: CEOR 5*, 223.

Starc, A. and R. J. Town (2020). Externalities and benefit design in health insurance. *The Review of Economic Studies 87*(6), 2827–2858.

Tables

Table 1: Summary statistics

	N	Mean	StDev	Min	Max
Panel A - Financials					
Operating surplus/deficit	1491	1958	19582	-239284	125004
Surplus/deficit for the year	1491	-2700	25486	-249654	283159
Comprehensive income/expense	1491	-1299	28639	-252374	272746
Operating surplus/deficit					
East of England	32	-4375	20352	-82237	27608
London	189	5336	28053	-136516	110206
Midlands	347	-1178	22455	-239284	50605
North	448	2892	15963	-92484	125004
North East and Yorkshire	57	-476	18523	-56365	44430
North West	56	795	21735	-72672	66537
South	283	2764	12497	-59614	49803
South East	40	5984	21412	-69638	50599
South West	34	2691	13930	-28121	41226
Panel B - Prescribing					
Hepatitis C Numerator	983	301	935	0	19600
Hepatitis C Denominator	984	99	43	29	308
Hepatitis C Value	983	304	1055	0	26724
Multiple Sclerosis Numerator	3440	1199120	4334723	0	64716001
Multiple Sclerosis Denominator	3442	99	41	12	305
Multiple Sclerosis Value	3440	1201335	4118348	0	59181359
Prescribing value					
Alemtuzumab	617	1	2	0	19
Dasabuvir	780	315	1177	0	26724
Dimethyl fumarate	786	1121	1940	1	35716
Fingolimod	634	1	1	0	10
Glatiramer acetate	514	72	108	0	1018
Interferon beta-1a	442	8339076	8064179	19684	59181359
Interferon beta-1b (Extavia)	184	2422819	3909674	0	34610954
Ocrelizumab	46	3	4	0	27
Sofosbuvir	203	262	254	12	1559
Teriflunomide	217	8	10	0	59

Notes: Summary statistics of financial accounts, prescribing of innovative medicines and consultant episodes for a range of diseases. Panel A reports the entire available 2009/10 to 2019/20 period for about 150 trusts, in thousands, including a tabulation by region. Panel B 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 and the value is the ratio between the two. The lower part of panel B tabulates by treatment.

Table 2: Treatments by condition and approval date

Treatment	Condition	Date Approved	Appraisal
sofosbuvir	Hepatitis C	Feb-15	TA330
dasabuvir	Hepatitis C	Nov-15	TA365
natalizumab	Multiple Sclerosis	Aug-07	TA127
fingolimod	Multiple Sclerosis	Apr-12	TA254
teriflunomide	Multiple Sclerosis	Jan-14	TA303
alemtuzumab	Multiple Sclerosis	May-14	TA312
dimethyl fumarate	Multiple Sclerosis	Aug-14	TA320

Table 3: Main results - Prescribing

	(1) OLS	(2) OLS lags	(3) FE	(4) FE lags	(5) Hep C only	(6) MS only
Std. operating surplus/deficit	0.160***	0.287***	0.036*	0.056**	0.176***	0.034
	(0.026)	(0.071)	(0.018)	(0.024)	(0.054)	(0.028)
N	2,698	2,476	2,695	2,474	528	1,942
Lags	No	Yes	No	Yes	Yes	Yes
Trust FE	No	No	Yes	Yes	Yes	Yes
Quarter FE	No	No	Yes	Yes	Yes	Yes
Condition FE	No	No	Yes	Yes	No	No
Treatment FE	No	No	Yes	Yes	Yes	Yes

Notes: Regression results of 1, dependent variable is the logarithm of prescribing. Columns (1) and (2) use OLS where the second specification adds two lags of the standardised operating surplus/deficit. Columns (3) and (4) apply all fixed effects. Column (5) presents the results for hepatitis C prescribing only and Column (6) for multiple sclerosis only. Standard errors clustered at the level of quarter. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Robustness - Prescribing

	(1) No lags	(2) 3 lags	(3) 5 lags	(4) 2-way cluster
Std. operating surplus/deficit	0.166***	0.153***	0.179***	0.166**
	(0.054)	(0.045)	(0.050)	(0.072)
N	504	572	480	504
Lags	0 lags	3 lags	5 lags	2 lags
Trust FE	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes
Treatment FE	Yes	Yes	Yes	Yes

Notes: Regression results of 1, dependent variable is the logarithm of prescribing and the sample is restricted only to Hep C medicines prescribing. Standard errors clustered at the level of quarter in all but column (4), where they are clustered both at the provider and the quarter level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Summary statistics for CVD and HDD prevalence and FCE by GP

Variable	Obs	Mean	Std. Dev.	Min	Max
Finished Consultant Episodes - Multiple Sclerosis	53,989	5.304284	9.151855	0	107
Finished Consultant Episodes - Hep C	53,989	0.1809072	0.7294146	0	40
Atrial Fribrillation Prevalence	53,898	1.80759	0.9418601	0	28.71622
Coronary Heart Disease Prevalence	53,900	3.198925	1.228106	0	48.55072
Cardiovascular Disease Prevalence	47,320	1.318067	0.9888878	0	60
Heart Failure Prevalence	53,893	0.819864	0.451691	0	14.75
Left Ventricular Systolic Dysfunction Prevalence	33,634	0.3051632	0.2732142	0	5.56
Hypertension Prevalence	53,902	14.1023	3.904645	0	190.5797
Stroke and Transient Ischemic Attack Prevalence	53,900	1.7485	0.7994622	0	26.67
Chronic Kidney Disease Prevalence	53,897	4.047324	2.074366	0	34.43
Cancer Prevalence	53,901	2.630459	1.132378	0	28.26087

Notes: Summary statistics of prevalence of CVD and HDD by GP and FCE for Hep C and MS by GP. Table reports data available 2013/14 to 2019/20 period for approximately 6,800 GPs. Prevalence is presented in percentage points, i.e. number of patients divided by the relevant patient population multiplied by 10.

Table 6: Exogeniety of Hep C and MS with CVD and HDD

	(1) FCE_MS	(2) FCE_HepC
Atrial Fibrillation Prevalence	-0.0145	0.0163
	-0.117	-0.193
Coronary Heart Disease Prevalence	-0.0615	-0.265
	-0.17	-0.347
Cardiovascular Disease Prevalence	-0.013	0.0158
	-0.021	-0.0453
Heart Failure Prevalence	0.0823	-0.0117
	-0.0619	-0.145
Left Ventricular Systolic Dysfunction Prevalence	-0.00159	-0.0401
	-0.0226	-0.054
Hypertension Prevalence	-0.231	-0.127
	-0.234	-0.439
Stroke and Transient Ischemic Attack Prevalence	0.16	-0.164
	-0.135	-0.25
Chronic Kidney Disease Prevalence	-0.0075	
	-0.0587	
Cancer Prevalence		0.0491
		-0.184
GP Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: Regression results of 2, dependent variable is log of Finished Consultant Episodes (FCE) for MS (Column 1), and Hep C (Column 2). All prevalence variables are logged. Estimated with GP and Year fixed effects. Standard errors clustered at the level of GP in both. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figures

Figure 1: Density of operating surplus or deficit, winsorised fraction 0.01