Just What the Doctor Ordered: Understanding Prescriptions in the UK

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Abstract

Economic progress requires innovation, yet, once innovations are available, their adoption can be slow. This dissertation provides a novel case study: the speed of new drug adoption in the UK. I find that adoption delay is large and cannot fully be explained by patient need. This provides the first evidence of inefficiency in the adoption of new drugs and substantiates concerns about a 'postcode lottery' in UK medical prescriptions. Furthermore, I show that a previously unexplored factor, Electronic Health Record systems, can influence the speed of adoption. This provides evidence that information provision is critical to the adoption of innovation.

7489 Words

1 Introduction

Innovation is at the heart of economic progress. Yet, once innovations are available, their adoption is far from automatic. Speed of adoption of innovations, from hybrid corn (Griliches, 1957) to computers (Caselli and Coleman, 2001), can vary dramatically and slow adoption can be very costly to society (Comin and Hobijn, 2010).

This dissertation focuses on a particularly important example – the adoption of new drugs. I examine the adoption of three new diabetes drugs introduced at different times in the last decade, using monthly data from all of England's general practices. The dissertation makes three contributions. First, I document large and variable delays in new drug adoption across practices. Second, I demonstrate that a considerable part of this variation is inefficient as it cannot be explained by differences in demand for diabetes drugs across locations. This provides the first evidence, to the best of my knowledge, of inefficiency in the adoption of new drugs and substantiates concerns about a 'postcode lottery' in UK medical prescriptions.[1] Third, I exploit arguably exogenous variation in electronic health record systems ("electronic systems") to show that the way information on new drugs is disseminated to general practitioners (GPs) significantly changes the speed of adoption. This provides evidence of the importance of information provision in adoption of innovation and leads to clear policy implications to ensure efficient drug adoption across the UK.

Geographical variation in both innovation adoption and public service provision has been documented in many societies (Skinner and Staiger, 2007; Mays and Smith, 2009). The case of the UK is particularly interesting, because the state provides nearly all healthcare, and access to primary care is organised regionally. Geographical variation may therefore be exacerbated leading to serious consequences for people's health and welfare. Media and commentators often complain of a 'postcode lottery' in UK healthcare and prescriptions in particular (for example, "Postcode lottery in HRT medication" Stanton, 2022). My first contribution is to show that one important source of geographical variation in healthcare is the speed of adoption of new drugs; for the three drugs analysed, only 11% of practices prescribed within the first year of availability whilst 18% took over three years.

[1] The main body of work identifying the "postcode lottery" is the "Atlas of Variation" (Public Health England, 2019)

However, in order to ascertain whether this variation is inefficient, one first needs to isolate geographical variation in patient need for the drugs. This is my second contribution. I believe this is the first study on new drugs that achieves this separation, and provides evidence that inefficiency exists. I do this by exploiting a particular feature of a class of diabetes drugs which allows me to accurately control, via prescriptions of a prerequisite diabetes drug, metformin, for the number of patients for whom the new drugs would be appropriate. I then show that, after controlling for metformin, substantial variation can be explained by factors exogenous to patient need, including which electronic system was used by the practice alongside practitioner and local area characteristics, identifying inefficient variation.

Thirdly, I show the importance of information provision in reducing inefficiency in the delay of adoption of new drugs. Exploiting variation in the electronic system used, I find that practices using Microtest, as opposed to EMIS Health, were consistently 17.5% more likely to prescribe new drugs in any time period. This highlights the importance of information provision in the diffusion of innovation in healthcare, where doctors face uncertainty about the potential benefits of new technologies (McClellan, 1995).

The medical context of this dissertation is important. Type II diabetes presents a serious public health challenge. There are an estimated 3.4 million people diagnosed with type II diabetes in the UK and it costs NHS England £10 billion a year, of which 12% is spent on prescription drugs (Diabetes UK, 2019; NHS England, 2022a). This dissertation, therefore, contributes not only to the study of innovation adoption as a whole, but also to the understanding of *"the greatest epidemic in human history"* (Zimmet, 2017, p.7).

As a case study this dissertation contributes to a broad economic literature on the speed of adoption of innovation and its importance to economic growth (see survey by van Oorschot et al., 2018). Unlike most of this literature, which is concerned with the decisions of profit-maximising agents[2], this case study focuses on non-profit decisions by doctors. These decisions have been predominantly modelled in two ways: learning by doing (Jovanovic and Nyarko, 1996; Gong, 2017) and patient-physician matching (Dickstein, 2018; Crawford and Shum 2005). Of central importance to these models is information, to which this dissertation provides empirical evidence.

[2] See Skinner and Staiger (2015) for a discussion of this

Evidence of the importance of information in the adoption of new drugs stems from seminal work by Coleman et al. (1957), who found that practitioners who frequently interacted with other practitioners prescribed new drugs faster. More recent work by Arrow et al. (2020) looked at how access to a drug database affected US physicians' adoption of cholesterol drugs. This dissertation is similar to the work of Arrow et al. in that it analyses the impact of information provision from software, but there is an important difference. In the US, physician's decisions involve both their own profit and what their patient can afford (Jacobson et al., 2017), complicated by different insurance schemes; the database's comparative advantage over other sources was in providing easy access to this information. This partly explains why use of the database only increased the speed of adoption of new *generic* drugs. In the UK, on the other hand, GPs' pay is fixed nationally, and all drugs cost the same to patients. This dissertation, therefore, isolates the impact of information provision on the medical, as opposed to financial, benefits of the drugs.

Finally, this dissertation contributes to two narrower fields. The first has analysed the impact of electronic systems in healthcare, noting a surprising lack of cost reduction following their introduction (Agha, 2014; Dranove et al., 2014). This dissertation instead focuses on the *differences between* electronic systems and how they affect prescribing, showing that they are significant in determining drug adoption. The second is international medical policy literature, analysing the characteristics of practitioners who prescribe new drugs quickly (Bourke and Roper, 2012; Huskamp et al., 2013; Lo-Ciganic et al., 2016; Zhang et al., 2019, amongst others). These papers share the same flaw - they do not control for the disease profiles of patients. When analysing the characteristics, therefore, it is unclear whether they are correlated with variation stemming from patient need (*efficient* variation), or from other factors (*inefficient* variation) severely limiting the studies. This dissertation, using metformin as a control, is the first to be able to identify the characteristics of practices associated with inefficient variation, and is the first to analyse new drug adoption in the UK, providing valuable policy insights.

2 Background

2.1 Flozins

This dissertation focuses on uptake by GPs of three new drugs, known as flozins, for the treatment of type II diabetes. The drugs - dapagliflozin, canagliflozin and empagliflozin – were

first licensed in England in November 2012, November 2013 and May 2014 respectively (EMA, 2012, 2013, 2014). The drugs were then approved for use in the NHS in England; however, the exact date when they first became available for GP prescription is unknown as the relevant records only cover the last six years (Medicines Complete, 2023). This does not pose an issue as I choose an econometric method where only the first recorded prescription of the drug matters: see Section 4.

In the time-period analysed: January 1st, 2012, to December 31st, 2019, 240 new drugs were licensed for use in England[3]. Analysing the uptake of all of these drugs would not be computationally possible, nor particularly insightful. For a drug to provide a useful case study for the diffusion of innovation it needs to fulfil two key criteria, which all three of these drugs do.

First, the drug needs to represent an unambiguous improvement from the status quo. The three drugs selected for analysis have become a mainstay treatment for type II diabetes (NICE, 2015b), as they have been shown not only to reduce blood glucose but also the risk of cardiovascular disease (Shubrook et al., 2015). This is observed empirically: by December 2019, 99% of practices had prescribed dapagliflozin and empagliflozin, whilst 91% had prescribed canagliflozin (see Table 3a).

Second, there needs to be a control for the number of patients for whom the drug is appropriate. In this case, clinical guidance from National Health and Care Excellence (NICE) recommends prescription of each of the three drugs in combination therapy with another well-established type II diabetes drug, metformin (NICE, 2013; NICE, 2014; NICE, 2015a; NICE, 2015b). The number of items of metformin, therefore, represents the relevant patient demand for the drug.

Together, these two criteria allow the classification of variation of adoption delay as efficient or inefficient. I define as "inefficient", delays in the adoption of a beneficial drug that are not explained by variation in patient need. Here, therefore, adoption variation not explained by metformin variation is inefficient.

This is the first such time, to my knowledge, that this distinction has been drawn. In addition, despite the clinical importance of these drugs, according to a systematic literature review by

[3] Own calculation using Hwang et al., 2020 and EMA, 2023

Medlinskiene et al. (2021), the variation in speed of uptake of these drugs has not previously been analysed in any country.

2.2 English Primary Care

Primary care in England, which is provided by GPs, has a complex structure. The critical factor to understand is that GPs, who manage practices, are independent contractors. Before July 2022, they were contracted by their local Clinical Commissioning Group (CCG), who managed primary care commissioning in England (NHS England, 2015; NHS England, 2022b). In addition, GPs' pay is not dependent on the prescription of drugs. This is important as it shows that a GP's decision whether to prescribe a new drug is solely determined by the GP's perceived benefits of the drug to the patient, not their own profit or costs to the patient. Information provision via electronic systems matters, therefore, as it informs this perceived benefit.

2.3 Electronic systems

The primary purpose of an electronic system is to manage patients' electronic health records (NHS, 2023). Some systems provide additional functionality to assist with a variety of GP activity, including clinical decision support systems (Dranove et al., 2014), that provide prescribing advice. The influence of the systems on prescribing may arise from: information provision on new drugs in the form of a drug dictionary (as in Arrow et al., 2020); which individual drugs are recommended based on a patient's health record (Hsieh et al., 2004); and the way in which information is displayed, nudging GPs towards certain prescribing decisions (Mackenna et al., 2020).

There are four main electronic systems used by GPs in the observed time period. These are EMIS health, SystemOne, Vision 3, and Microtest (usage described in Table 3d). Understanding in detail the differences in these systems would be useful for identifying which features drive faster prescribing. Complete information on this is not, however, available. There is some information published, by the businesses, on what their electronic systems include: EMIS Health and SystemOne are not described as including prescribing decision support (EMIS Health, 2023; The Phoenix Partnership, 2023); by contrast, Vision 3 has "*embedded prescribing support*" and Microtest offers a "*fully integrated drug dictionary and decision support system*" (Cegedim Healthcare, 2023; Eva Health Technologies, 2023). Combining this evidence with previous research highlighting how differences in systems can affect generic

prescribing rates (Mackenna et al., 2020), suggests that differences in the information provided by the systems could affect new drug adoption.

There is no publicly available information on what GPs consider when choosing an electronic system, raising concerns about endogeneity in selection. However, given that the primary purpose of electronic systems is to manage health records and integrate with other forms of healthcare, and that prescription advice is one of a number of additional services that these systems can provide (Dranove et al., 2014), it is unlikely that the prescription advice service is the primary reason a GP practice would choose one system over another. In conversation with three GPs, all said the prescription advice service was not considered in their choice. The choice is influenced by CCGs, discussed below. When controlling for CCG, therefore, the choice of electronic system is likely uncorrelated with the natural inclination of a practice to prescribe new drugs quickly, making the system used arguably exogenous. This is discussed further in Section 5.1.

2.4 Clinical Commissioning Groups

There were 217 CCGs in December 2012 (NHS Digital, 2021), covering regional groups of practices in the UK. The number of practices per CCG ranges from 5 to 185, with a mean of 39. Numerous studies have found that prescription behaviour varies by CCG (Walker et al., 2018; Zheng et al., 2020; Curtis et al., 2020) and CCGs have been seen as a key driver of the "postcode lottery" in healthcare (Smith and Haeney, 2020). This is for two reasons: first, CCGs are regional entities and can therefore capture differences in healthcare needs of local areas reflected in prescribing; second, CCGs provide local guidance on prescribing to their contracted GPs (NHS England, 2015). CCGs, importantly, also provide guidance on the choice of electronic system. The fact they advise on the choice of electronic system is supported empirically: only one electronic supplier is used by all of the practices in 39% of CCGs, whilst fewer than 6% have practices using all four systems. This contributes to the endogeneity concerns highlighted above; therefore, I use CCG fixed effects. The electronic system used is still found to consistently affect the speed of uptake of new drugs, see Sections 5.1 and 6.3.

3 Data and Descriptive Evidence

3.1 Prescription Data

Data on prescriptions was retrieved from two sources: the Practice Level Prescribing Dataset (PLPD) and the English Prescribing Dataset (EPD), both provided by the NHS (NHS Digital, 2020; NHSBSA, 2023). Between them, these datasets provide monthly data on every prescription by every practice in England: the EPD was created to replace the PLPD dataset from 2014. Downloading all 514GB of data at once was not possible. Therefore, I downloaded monthly datasets from November 2012 to December 2013 from the PLPD and from January 2014 to December 2019 from the EPD in groups, processing them using Python.

I reformatted the data to record the number of prescriptions made for each of the four drugs (the three flozins and metformin) by each of the 7,716 practices, in each of the 86 months contained in the dataset. From this, "First prescription" dates were calculated for each of the practices, reported in Table 3a.

Table 3a: Descriptive Statistics, Flozins

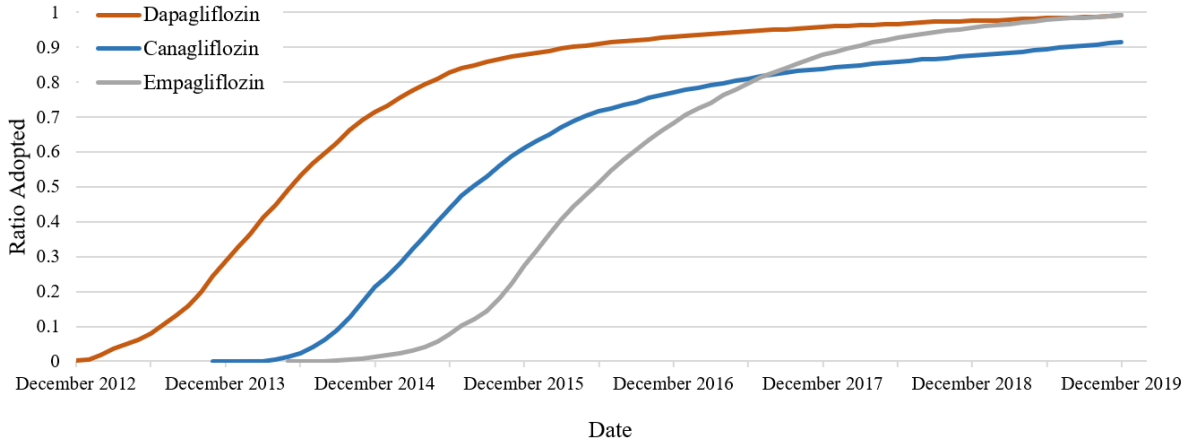
		First English	Months Until First Prescription			Ratio Adopted
Drug Name	Licencing Date	Prescription	Mean	Median	S.D.	by Dec 2019
Dapagliflozin	November 2012	December 2012	20.23	18	12.43	0.990
Canagliflozin	November 2013	February 2014	24.84	21	14.35	0.913
Empagliflozin	May 2014	August 2014	27.84	25	11.48	0.990

Notes: Measures under "Months until first prescription" are conditional on a prescription occuring, for practices that remained open during the observed period. They are calculated as the number of months after licencing; see Section 2.1 for a discussion of this. Ratio Adopted means the ratio of practices that have prescribed the drug by the end of December 2019.

This showcases three important results that motivate this dissertation. First, there is large variation in the adoption delay for each of the three drugs; the interquartile ranges of the three delays are all above a year. Second, the mean adoption delay isaround two years – given there are over three million patients with diabetes, this represents a significant failure in public health. Finally, almost all practices prescribed the drugs by December 2019, supporting the assumption that these drugs mark an improvement on the status quo[4]. The time trends for the uptake of the drugs can be seen in Figure 3b:

[4] Notably, Canagliflozin was the least popular with only 91% uptake. This is likely due to it being the least efficient of the three at reducing blood glucose (Hsia et al., 2016)

Figure 3b: Flozin Uptake Curves



Notes: Ratio Adopted is the ratio of practices which have prescribed the drug at least once, to total open practices, in each month.

These curves have an "S-shape", which has been well documented in the innovation literature as a result of slow information diffusion (Geroski, 2000). They also show that uptake was still increasing, slowly, at the end of the period; for each of the drugs over 10 first prescriptions were made in December 2019. Therefore, the mean and variance of adoption delay are slight underestimates of their true values.

The time to prescribe each of the drugs is also correlated, between 0.15 and 0.25, significant at the 1% level. This suggests that some factor, at practice or location level, consistently affects delay, motivating the study of electronic systems and characteristics.

3.2 Overview of Characteristics

Summary statistics are provided for the independent variables for the start, middle and end of the sample, in Table 3c. Discussions of sources and data processing are in Section 3.3 and 3.4.

Table 3c: Summary Statistics of Independent Variables

Variable	November 2012		June 2016		December 2019	
	Mean	S.D.	Mean	S.D.	Mean	S.D.
Practice Characteristics						
Metformin Items in 100s	1.84	1.20	2.12	1.42	2.72	1.90
Patients in 1000s	7.11	4.31	7.67	4.71	8.78	5.73
Patients over 65 in 1000s	1.20	0.89	1.33	0.99	1.54	1.18
GP Headcount	5.15	3.52	5.20	3.56	6.39	4.67
Admin Headcount*	11.6	6.87	12.5	8.03	14.0	10.2
Practitioner Characteristics						
Mean GP Age	47.6	7.42	47.3	7.31	46.7	7.22
Ratio of Female GPs	0.45	0.26	0.48	0.26	0.51	0.25
Ratio of GPs Educated outside the UK	0.32	0.35	0.32	0.34	0.35	0.32
Local Area Characteristics						
Rural Practice Indicator	0.14	0.35	0.15	0.35	0.15	0.36
Average Income in £1000s	42.3	10.0	42.3	10.0	42.5	10.0
IMD score	26.3	17.4	26.3	17.4	25.9	17.2
Observations	7716		7482		6794	

*There are missing observations for admin headcount: 19 in 2013, 10 in 2016 and 2 in 2019.
Notes: S.D. is standard deviation. The number of observations falls over time due to practices closing.

At the start of the sample, in November 2012, there were 7716 practices, falling to 6794 by December 2019, as 922 practices closed. There were, in 2013, 211 practices for which no data on the electronic system was available, the impact of this is discussed in Section 3.3. By December 2019, however, as the data is more complete, there were only 22 such practices.

For practice characteristics, as opposed to practitioner or local area characteristics, there is reasonable time variation. The number of metformin prescriptions, importantly, increases 48% and so does its variation. As metformin enables the identification of efficient variation, by representing patient need, including time-variation in the econometric estimation is important, so duration analysis is used (see Section 4).

3.3 Practice and Practitioner Characteristics

Practice and practitioner characteristics were all sourced from the NHS. The key variable of interest is which electronic system each practice used in each year. Summary statistics are provided below, in Table 3d. The main systems are EMIS Health and SystemOne, with 87%

market share in 2015, growing to 95% by the end of the sample. The minor systems, Vision 3 and Microtest have a sizeable but decreasing numbers of users, due to practices switching system and practices closing. The overall number of users is decreasing as practices closed.

Table 3d: EHR System User Counts By Year

Software System	2015	2016	2017	2018	2019
EMIS Health	4023	4197	4133	4032	3925
SystemOne	2471	2564	2569	2559	2524
Vision 3	898	585	455	337	259
Microtest	107	95	87	70	59
Total Observations	7499	7441	7244	6998	6767

Notes: Table contains the number of users of each Software Supplier, by year. The data is only available from 2015 onwards.

Data is only available on the electronic system used from 2015 onwards (NHS Digital, 2022). This poses an issue as all three drugs were approved before 2015. To allow for an analysis of these systems, the electronic system the GP used in 2015 was assumed to be the electronic system they used before that, whilst for observable data the electronic system is updated yearly. This assumption is justified for three reasons.

First, amongst practices which remained open throughout the five observed years, only 11.2% changed supplier. The period without data spans just over two years, so change is likely infrequent. Second, removing practices which switched system during the observed period does not change the results, suggesting that neither would removing those that switched before 2015, see Section 6.2. Third, whilst this issue is relevant for Dapagliflozin, as 71% of practices had prescribed it before 2015, for Empagliflozin only 1.3% had, meaning the results are extremely unlikely to be biased. In Section 5.1, I find that the effect of each system is consistent across all three drugs, suggesting that unobserved changes are not a source of bias; otherwise, the effects of at least one of the systems on the adoption of Empagliflozin and Dapagliflozin would be inconsistent.

Data on the remaining practice and practitioner characteristics was derived from two sources: the General Practice Workforce database and the Patients Registered at a GP Practice database, whilst data identifying whether the practice was a General Practice as opposed to a school or prison, for example, came from GP and GP Related Data (NHS Digital, 2021; NHS Digital, 2023a; NHS Digital, 2023b). The data is available yearly over the observation period.

All the data had formatting issues, dealt with on a case-by-case basis, however, there was one substantial data issue. 12.2% of practice-year combinations did not have a reported value for at least one of the characteristics. I used linear interpolation to fill the missing datapoints to retain sample size. Dropping these practices does not affect the results (see Section 6.2).

I chose to include characteristics to identify inefficient variation and remove omitted variable bias. These include the total number of patients registered, and GPs and administrative staff working, at the practice. Data on the individual GPs had to be aggregated to practice level; this involved calculating the mean age of GPs and the proportions of female GPs and GPs who had their medical education outside of the UK. As discussed in Section 2.4, dummies for the 217 CCGs (regional governing bodies) were included to remove endogeneity concerns.

3.4 Local Area Characteristics

The final data source used was the Office for National Statistics (ONS), to provide data on local area characteristics (ONS, 2015, 2018, 2023). Practices were linked via their postcode to determine whether the practice was rural, as defined by the ONS, and what the average income and Index of Multiple Deprivation (IMD) scores were for the local area. 90% of postcodes are associated with one practice whilst the number of practices per local area varies, with an average of 4 practices in each. The rural indicator was from 2011, whilst the average income and IMD score came from 2015. A higher IMD score indicates higher levels of deprivation. As with practice data, these were included partly to remove omitted variable bias but also out of interest, to identify inefficient variation.

4 Methods

This dissertation is concerned with the speed of uptake of new drugs, in order to: (a) document variation, (b) explore whether there is inefficiency present, and (c) analyse the role information plays. The outcome variable that I am interested in, therefore, is the time to prescribe a new drug. This dependent variable poses issues for standard econometric analysis, which are well dealt with by duration analysis, a form of maximum likelihood estimation.

The key advantage of duration analysis is that it allows for time-varying independent variables. In brief, duration analysis models compare the values of the independent variables for the practices which first prescribed, to those that have yet to prescribe, in each period (Cleves et al., 2010). This is not possible in a cross-sectional regression, which requires a single value for

the independent variables for each practice, taking months to prescribe as the dependent variable, see Section 6.3. Time-variation matters for two key reasons in my analysis. First, accounting for time trends in the metformin prescriptions is critical to being able to accurately identify inefficient variation. Second, some practices change electronic system over the observed time period; a cross-section would not be able to adjust for this and would therefore limit the reliability of the results.

Another important feature of duration analysis is that it is robust to right-censoring. This is present in the data in two forms: practices that close before having prescribed or have not prescribed before the end of the dataset's observations. This right-censoring can bias linear regressions of time to prescribe on covariates. Duration analysis assumes that censoring and the factors influencing prescription decisions are independent (Cameron and Trivedi, 2005). Whilst this assumption is very likely to hold, it is not directly testable, so further evidence is provided in Section 6.2, which supports the assumption.

This dissertation uses duration analysis. These models estimate the hazard rate, which, in this context, is the probability that a practice prescribes in period *t*, given that they have not prescribed up to *t*. The non-parametric form of the hazard rate is:

$$h_j(t) = g\left(t, \beta_0 + \boldsymbol{\beta_x x_j}(\boldsymbol{t})\right)$$

Here $h_j(t)$ represents the hazard of practice *j* at time *t*, which is given by the function $g\left(t, \beta_0 + \boldsymbol{\beta_x x_j}(\boldsymbol{t})\right)$, where $\boldsymbol{\beta_x}\, \boldsymbol{x_j}(\boldsymbol{t})$ represents the dot product of potentially time-varying covariates and their coefficients. In order to estimate the coefficients, I assume proportional hazards - this assumption is found to hold in Section 6.1. This means that the hazard rate takes the semi-parametric form:

$$h_j\left(t\middle|\boldsymbol{X_{sj}}(\boldsymbol{t}), \boldsymbol{X_{pj}}(\boldsymbol{t}), \boldsymbol{Z_j}, \boldsymbol{X_{cj}}(\boldsymbol{t})\right) = h_0(t) * exp(\boldsymbol{\beta_s X_{sj}}(\boldsymbol{t}) + \boldsymbol{\beta_p X_{pj}}(\boldsymbol{t}) + \boldsymbol{\beta_l Z_j} + \boldsymbol{\beta_c X_{cj}}(\boldsymbol{t}))$$

Where $h_0(t)$ is the baseline hazard function and $\boldsymbol{X_{sj}}(\boldsymbol{t}), \boldsymbol{X_{pj}}(\boldsymbol{t}), \boldsymbol{Z_j}, \boldsymbol{X_{cj}}(\boldsymbol{t})$ are, respectively, vectors of electronic system dummies, practice and practitioner characteristics, local area characteristics and CCG dummies. Only the local area characteristics are time-invariant. In Section 5, Results, coefficients are given in their hazard ratio form, $exp(\beta_x)$, as this has the

easy interpretation of multiplying the baseline hazard, similar to an odds ratio in logistic models.

Some similar papers use parametric duration analysis, such as Bourke and Roper (2012), which requires an assumed functional form of the baseline hazard, $h_0(t)$. This can increase efficiency if the functional form is correct. I use the semi-parametric Cox proportional hazards model (Cox, 1972). This is for three reasons: first, if the functional form of the baseline hazard is mis-specified in parametric analysis, then the estimates of the coefficients will be inconsistent (Cleves et al., 2010). The Cox model, being semi-parametric, allows a fully flexible baseline hazard model. The second advantage of the Cox model is that only periods in which a first prescription is made contribute to the estimation of the coefficients. As there is limited data availability on the first month each drug *could be* prescribed (see Section 2.1), this means only the first month when each drug *was* prescribed, matters for the results. Finally, Cox models are more robust to unobserved heterogeneity than parametric models (Dolton and van der Klaauw, 1995).

5 Results

I estimate Cox proportional hazards' models, the results of which are reported in Table 5a. Robust standard errors are used. In the table, hazard ratios are reported for interpretation: an increase in the independent variable of one unit multiplies the hazard rate by the hazard ratio. Therefore, I am testing against the null hypothesis that the coefficients are one, rather than zero.

The results explore the variation in speed of uptake documented in Section 3.1, by analysing the role of electronic systems (5.1) and characteristics (5.2), thereby identifying causes of inefficient variation (5.3).

Table 5a: Cox Models for Delays in New Drug Adoption

Variables	Dapagliflozin	Canagliflozin	Empagliflozin
Electronic System Dummies			
Reference: EMIS Health (N=4023)			
SystemOne (N=2471)	0.980	0.954	1.041
	(-0.71)	(-1.32)	(1.05)
Vision 3 (N=898)	1.105**	1.111*	1.109*
	(2.59)	(2.54)	(2.30)
Microtest (N=107)	1.175***	1.116*	1.234***
	(3.51)	(1.98)	(3.36)
Practice Level Characteristics			
Metformin Items in 100s	1.153***	1.164***	1.169***
	(11.11)	(12.06)	(13.54)
Patients in 1000s	1.031***	1.013*	1.019**
	(5.06)	(2.01)	(3.13)
Patients over 65 in 1000s	1.116***	1.025	1.014
	(4.40)	(0.96)	(0.59)
GP Headcount	1.011	1.013	0.995
	(1.03)	(1.31)	(-0.51)
Admin Headcount	0.996	0.999	0.998
	(-1.35)	(-0.33)	(-0.52)
Practitioner Characteristics			
Mean GP Age	1.005	0.993	1.024
	(0.31)	(-0.45)	(1.65)
Mean GP Age Squared in 100s	0.995	1.004	0.973
	(-0.33)	(0.30)	(-1.96)
Ratio of Female GPs	0.907*	0.925	1.065
	(-1.98)	(-1.49)	(1.29)
Ratio of GPs Educated Outside	1.163***	1.075	1.204***
the UK	(3.70)	(1.78)	(4.69)
Local Area Characteristics			
Rural Pratice	0.912*	0.874***	0.825***
	(-2.51)	(-3.44)	(-5.16)
Average Income in £1000s	1.005*	1.002	1.007**
	(2.42)	(1.13)	(3.13)
IMD Score	0.997**	0.997*	0.996***
	(-3.08)	(-2.40)	(-4.22)
Observations	165499	223372	232493

Significance: *p<0.05 **p<0.01 ***p<0.001

Notes: Exponentiated coefficients are used for interpretation; t statistics in parentheses, calculated using a Wald test of the null hypothesis: $\beta=1$ against $\beta\neq1$, using robust standard errors. All Models include CCG Fixed Effects (not reported). For the electronic systems, N is the number of users in 2015. Observations represent the number of months before prescribing a new drug summed across each practice; hence, for drugs with longer average delays, there are more observations.

5.1 The Role of Electronic Systems

The results, reported in Table 5a, show that the users of different electronic systems had significantly different hazard rates. This implies that differences in what and/or how information is provided are significant in determining the speed of new drug uptake.

Main Systems

SystemOne and EMIS Health share a duopoly in the GP electronic system market, with 87% of practices included in our analysis using them in 2015, rising to 95% by the end of 2019. There were no significant differences in hazard ratios between practices using these systems for any of the drugs, suggesting that they did not differ in the information provided.

Minority Systems

Practices using Vision 3 and Microtest, the two minority systems, were consistently more likely to prescribe a new drug in any time period than users of EMIS Health. For Vision 3 users, the hazard rate was 11% greater than for practices using EMIS Health, for each drug. This suggests that Vision 3 consistently improved information provision on new drugs to practitioners, which fits with the story of *"embedded prescribing support"* (Cegedim, 2023). Microtest had larger effects: the hazard rates range from 11.6% to 23.4% greater than for EMIS. Again, Microtest specifically advertises their drug database and inbuilt decision support system (Eva Health Technologies, 2023), which may contribute to this finding.

Using Z-tests to perform pairwise comparisons of the coefficients of each system across the three drugs, the null hypothesis that the hazard ratios are equal is not rejected, showing that the electronic system used matters consistently. Z-tests are not perfect in this scenario: they assume that the covariance of the coefficients is 0, which is likely to be violated on regressions run on the same dataset. To account for this, a test using seemingly unrelated estimation is used in Section 6.3, which is robust to this issue. The same results are reached, providing further evidence that the effect of each system is consistent. This finding is important as not only does it show that information matters consistently, it also allays concerns arising from pre-2015 data availability, as discussed in Section 2.3.

There is, however, a potential concern about endogeneity: the practices which chose Vision 3 or Microtest may have already had a predisposition to prescribe new drugs quickly. I consider

that this is unlikely, for three reasons. First, there are multiple controls at practice level, which capture most of the differences between practices. Second, I include dummies for the local CCG, which capture potential regional biases in system choice and prescribing alongside direct advice on the systems by the CCG. There are, however, known issues with using fixed effects to control for endogeneity in duration analysis models (Greene, 2002; Allison, 2002), so I run linear fixed effects regressions in Section 6.3, where the same qualitative effects of the systems are found. Finally, as discussed in Section 2.3, the choice of electronic system is largely based on factors other than its information provided on new drugs, so there is no good reason to think that practices that prescribe quickly specifically choose one system over another.

To summarise, the data shows that the electronic systems used by GPs have a significant effect on how early they adopt the new drugs. This effect is stable across all three drugs and is economically significant: switching to a different information system can increase the speed of adoption of new drugs by up to 23%, corresponding to 5 months on average. This provides important evidence that information provision makes a substantial difference to new drug adoption.

5.2 Practice, Practitioner and Local Area Characteristics

Regressions in Table 5a include practice, practitioner, and local area characteristics primarily as controls. However, they are of interest in and of themselves. Unlike the electronic systems, it is more likely that these characteristics suffer from endogeneity. For example, doctors who are more inclined to prescribe new drugs may choose to work in busy urban areas: a selection bias for the rural practice variable. Whilst previous work has attempted to assign causal interpretations to these correlations[5], I will not, as the endogeneity issues are too large. Instead, as metformin is controlled for, the results document further inefficient variation (discussed below in Section 5.3), as well as helping determine which characteristics are associated with adoption delay.

Two of the practice characteristics included have significant effects: the number of patients for all three drugs and the number of patients over 65 for Dapagliflozin. Interestingly, neither GP headcount nor number of administrative staff has a significant impact on the time to prescribe;

[5] see Bourke and Roper (2012), Chressanthis et al. (2012), Huskamp et al. (2013) amongst others

this differs from findings in other papers which do not control for patient demand or information provision (Bourke and Roper, 2012; Huskamp et al., 2013).

Using summary measures for practitioner characteristics, I find that having a larger ratio of both male and internationally educated doctors increases the speed of prescribing Dapagliflozin, whilst this is only true for the internationally educated for Empagliflozin. The role of international doctors has not been previously explored in the literature (see survey by Medlinskiene et al., 2021), however, without further exploration, it is not possible to give this a robust causal interpretation.

Local area characteristics are also important determinants of prescribing speed. I find practices in rural, poorer, and more deprived areas are significantly slower to prescribe new drugs. Whilst it could be that rural areas prescribe new drugs more slowly due to reduced information access, as hypothesised by Chressanthis et al. (2012) amongst others, it could also be a sample selection bias as discussed above.

5.3 Evidence of Inefficient Variation

The most important characteristic included is metformin prescriptions, as this serves to distinguish efficient and inefficient variation. It makes this distinction by representing patient need, as metformin is a prerequisite for the prescription of flozins (NICE, 2015b). Critical to this is the idea that variation can be *efficient* if it is a product of differences in patient need at each practice. Estimations that do not control for patient need, therefore, cannot determine whether variation in the delay is efficient or inefficient. Unsurprisingly, the number of metformin prescriptions is highly significant in determining speed of adoption. This distinction has not been made in the literature before but is critical for both interpretation of the impacts of the characteristics and policy implications. That identifiable characteristics are significant, after controlling for efficient variation, highlights the inefficient variation present in the adoption of new drugs. In particular, the electronic system used, arguably exogenous to patient drug demand, has a consistent and significant impact on the time to prescribe. This has immediate policy implications for improving information provision to GPs to reduce inefficient variation.

6 Robustness

6.1 Proportional Hazards

The principal assumption of the Cox model is proportional hazards: as the covariates change, the hazard rate changes multiplicatively, across all time periods. In these models, the concern is that the effect of the electronic systems may change over time, violating this assumption. To test for this, I use the Schoenfeld residuals test (Grambsch and Therneau, 1994). The test examines the relationship between the scaled Schoenfeld residuals and time, with the null hypothesis of no correlation. Table 6a reports the results: the assumption of proportional hazards appears to hold for the electronic system dummies.

Table 6a: Grambsch and Therneau Proportional Hazards Test

	Dapagliflozin	Empagliflozin	Canagliflozin
Electronic System Dummies			
Reference System: EMIS Health			
SystemOne	0.019	-0.011	0.017
	(0.094)	(0.346)	(0.142)
Vision 3	-0.009	0.007	-0.009
	(0.428)	(0.546)	(0.502)
Microtest	0.001	0.002	0.004
	(0.905)	(0.886)	(0.734)

Notes: Values are estimated linear coefficients of Schoenfeldt (1982) residuals against time. P values in brackets calculated using a chi-squared test. No significant values suggest that there is no omitted time variable for the suppliers, so the proportional hazards assumption is satisfied.

6.2 Sample Restriction Tests

Throughout this dissertation I have referenced four groups of practices that could pose issues for the robustness of the results. To deal with this, I perform four sample restrictions, specified below. The results of these restrictions are in the Appendix: Table A1. Whilst two restrictions make the coefficient on Microtest for Canagliflozin insignificant, the magnitudes of the estimates stay consistent. In general, as there are no major changes in the magnitudes of the coefficients, I conclude that none of the four groups of practices are driving the results.

The first, and largest, restriction removes the 942 practices, representing 12.2% of the sample, which reported “NS” or “ND” values for any variable as discussed in Section 3.2. There were no significant changes.

The second restriction removes the 866 practices that changed their electronic system during the observed time period, as referenced in Section 5.1. These are of concern for two reasons: first, if the timing of the changes were coincidental with a period where many first prescriptions were made, the results may be biased. Second, showing that these practices do not significantly alter the results provides further evidence that the lack of data pre-2015 is inconsequential. This restriction made no significant changes to the results.

The third restriction deals with the 922 practices that closed before 2020. As discussed in Section 4, duration analysis models require the assumption of random censoring, and, although it seems unlikely, it is possible that a practice closing is correlated with its underlying propensity to prescribe new drugs. The coefficient of Microtest for Canagliflozin becomes insignificant following this restriction, however, there is only a 2% change in the magnitude, so I conclude that practices which closed do not bias the results.

The final restriction keeps only practices which consistently prescribed over 10 items of metformin, dropping 305 practices. As with the previous restriction, the coefficient of Microtest for Canagliflozin becomes insignificant but remains similar in magnitude. No other coefficients significantly change. This provides robust evidence that practices which do not have the opportunity to prescribe the new drugs are not driving the results.

6.3 Linear Models

I estimate linear fixed effects models to provide robustness to the preferred duration analysis models, as they can fully control for the endogeneity concerns arising from CCGs, as referenced in section 5.1. The linear models are estimated using the 6767 practices which remained open and had observations for each of the variables. The dependent variables for the three regressions are the log of the delay, in months, between licensing of the drug and its adoption. In this specification, unlike duration analysis, time-varying variables are not possible. Hence, for vectors of the dummy variables, the electronic systems and CCGs, values from 2015 are used. For continuous variables, the mean value is used. The resulting three regressions have the form:

$$\ln\left(delay_{d,j}\right) = \beta_0 + \boldsymbol{\beta_s} \boldsymbol{X_{sj}^{2015}} + \boldsymbol{\beta_c} \boldsymbol{X_{cj}^{2015}} + \boldsymbol{\beta_p} \boldsymbol{\bar{X}_{pj}} + \boldsymbol{\beta_l} \boldsymbol{Z_j} + \epsilon_j$$

Here $delay_{d,j}$ represents the adoption delay, measured as months between licencing and adoption, for drug *d* for practice *j*. $\boldsymbol{X_{sj}^{2015}}, \boldsymbol{X_{cj}^{2015}}$ represent the vectors of dummy variables for the electronic system and CCG of practice *j* in 2015, $\boldsymbol{\overline{X}_{pj}}$ represents the vector of mean values of practice and practitioner characteristics, and $\boldsymbol{Z_j}$ represents the local area characteristics.

Whilst direct quantitative comparisons with duration analysis cannot be made, some general comparisons can: a duration analysis hazard ratio greater than one corresponds to a negative linear coefficient (a practice that has a *larger* hazard rate should take *less* time to prescribe) and relative magnitudes should stay similar. The results are below in Table 6b.

Table 6b: Linear Models of Adoption Delay

Variables	Log Dapagliflozin Delay	Log Canagliflozin Delay	Log Empagliflozin Delay
Electronic System Dummies			
Reference System: EMIS Health			
SystemOne	-0.020	-0.018	-0.006
	(-1.49)	(-1.38)	(-0.33)
Vision 3	-0.052**	-0.054**	-0.052**
	(-2.74)	(-2.85)	(-2.65)
Microtest	-0.129***	-0.116**	-0.176*
	(-3.45)	(-2.98)	(-2.13)
N	6767	6767	6767

Significance: *p<0.05 **p<0.01 ***p<0.001

Notes: Robust standard errors used. Models all include practice, practitioner and local area characteristics, alongside CCG fixed effects (not reported). N represents the number of practices that remained open throughout the observed period.

The results are, reassuringly, similar to the Cox models' results in both direction of travel and comparative magnitude: users of SystemOne were not significantly faster to prescribe than users of EMIS Health. Vision 3 and Microtest users were consistently significantly faster to prescribe, with Microtest users being the fastest overall.

The linear models can also be used to provide robustness to the equality of coefficients tests in Section 5.1. The key issue with tests of equality of coefficients across the duration models is that the regressions are run using the same dataset on positively correlated dependent variables. This means the covariance of the coefficients is very likely non-zero. Seemingly unrelated estimation techniques, which can be used on the linear models, account for this (Weesie, 2000). The results of these tests of equalities of coefficients are, nevertheless, the same across duration analysis and linear estimations: each electronic supplier has a consistent effect on adoption delay, across all 3 drugs.

7 Conclusion

This dissertation analyses the speed of adoption of new drugs making three novel contributions. First, it documents the variation in the speed of uptake of new drugs in England, which has not previously been empirically studied. I find large, and highly variable, delays, with over 40% of practices taking over 2 years to prescribe. Second, it is the first to identify efficient and inefficient variation in the uptake of new drugs, finding that variation according to differences in patient need only explain a small part of the total variation. Finally, it is the first to analyse the impact differences between electronic systems have on the prescribing of new drugs. The information provided by these systems is found to be a key determinant of prescribing: use of Microtest as opposed to EMIS Health was found to increase the probability of prescribing new drugs by 17.5%.

This analysis is hampered by the poor quality of NHS-supplied data, reducing effective sample size as imputation methods are necessitated. More importantly, the lack of publicly available information on electronic systems means only general implications on the importance of information can be drawn. Further research into the differences between these systems could help identify what features aid new drug adoption, an important policy question.

Despite these limitations, the novel identification of efficient and inefficient variation in this dissertation uncovers a "postcode lottery" in new drug adoption. This has policy implications for promoting healthcare equality and improved information provision, particularly in rural and underprivileged areas. These findings not only contribute to improving healthcare quality, accessibility and equity in England but also to the study of innovation uptake by non-profit actors not commonly considered in economics. After all, innovations can only drive economic progress if they are adopted.

Appendix

Table A1: Sample Restriction Robustness

	No Restriction			Complete Records			Constant Electronic System			Remained Open			Metformin Items > 10		
Variables	Dap	Can	Emp	Dap	Can	Emp	Dap	Can	Emp	Dap	Can	Emp	Dap	Can	Emp
Electronic System Dummies															
Reference System: EMIS Health															
SystemOne	0.980	0.954	1.041	0.975	0.955	1.038	0.981	0.946	1.050	0.963	0.946	1.054	0.983	0.949	1.048
	(-0.71)	(-1.32)	(1.05)	(-0.78)	(-1.13)	(1.11)	(-0.66)	(-1.79)	(1.19)	(-1.02)	(-1.79)	(1.39)	(-0.63)	(-1.74)	(1.22)
Vision 3	1.105**	1.111*	1.109*	1.102*	1.133**	1.141**	1.140*	1.101*	1.157*	1.101**	1.106*	1.124*	1.105**	1.101*	1.122*
	(2.59)	(2.54)	(2.30)	(2.36)	(2.80)	(2.73)	(2.31)	(2.26)	(2.40)	(2.39)	(2.33)	(2.50)	(2.75)	(2.28)	(2.53)
Microtest	1.175***	1.116*	1.234***	1.177***	1.119*	1.229***	1.165**	1.112*	1.244***	1.184***	**1.114**	1.215**	1.192***	**1.098**	1.236***
	(3.51)	(1.98)	(3.36)	(3.23)	(1.99)	(3.32)	(2.51)	(2.01)	(3.46)	(3.27)	(1.88)	(3.21)	(3.69)	(1.72)	(3.55)
Observations	165499	223372	232493	144660	197940	205116	148625	204366	212076	147861	198839	206673	156856	214014	222768

Significance:*p<0.05,**p<0.01,***p<0.001. Notes: Dap, Can and Emp represent Dapagliflozin, Canagliflzoin and Empagliflozin respectively. Exponentiated coefficients are used for interpretation; t statistics in brackets, calculated using a Wald test of the null hypothesis: $\beta=1$ against $\beta\neq1$, using robust standard errors. The same controls as the main results are used. Bold hazard ratios have become insignificant.

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