Diffusion of new prescription drugs: evidence from the UK NHS primary care sector

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1. Introduction

Most developed countries have faced increasing health care expenditures over the last 30 years. In the UK and US medical expenditure has risen by 4% and 5.5% annually over the last few decades outstripping average annual national income growth (2.3% and 3% respectively). Technological change has been identified as one of the leading factors driving this growth in medical expenditure (Weisbrod, 1991; Newhouse, 1992) and this has generated a growing interest in understanding the diffusion process of new technologies in the health care sector.

Technological change in the health care market over the past decades has been rapid, broadening the capacity of patient treatment. One manifestation of this technological change is the number of drugs, surgical procedures and medical devises that are introduced every year in the global health care market. However, the introduction of such innovations does not necessarily lead to instantaneous widespread diffusion and there is usually a lapse between an innovation is introduced and its widespread use. Many examples exist for instance of positive results gained from clinical trials not having immediate effect on practice (Cutler and Huckman, 2003).

Against a rising interest in health technology as a contributory factor driving health care expenditure and in the process of diffusion itself this paper focuses on the up-take of new prescription drugs within the UK National Health Service (NHS) with two specific aims: First, the role of consumption externalities on the demand of new pharmaceuticals is analysed from a micro level perspective. Specifically the question of how prescription rates are influenced by the flows of information is assessed, as is the relationship between a physician's experience and the gain of information on the new product. Secondly, there is a set of regulatory elements that shape the practice environment. Hence, not only is a doctors' prescription behaviour influenced by the information they receive but also by the set of regulatory factors that provide additional incentives for a faster or lower uptake rate. Consequently, we study the diffusion of prescription drugs by focusing on two sets of factors: the factors that provide information to the doctor on the attributes of the drug and the environmental elements that condition prescription behaviour that are specific to the UK health care system.

Demand for pharmaceuticals has been studied in the literature analysing factors such as the decision of generic versus trade-name prescription (Hellersterein, 1998), the presence of doctor habit persistence (Johannesson and Lundin, 2001) or the existence of moral hazard in the prescription of drugs (Lundin, 2000). However, there is a lack of evidence on the demand for new prescription drugs and how they diffuse over time. The existing literature on diffusion in pharmaceutical markets analyses the process using aggregated variables (Berndt et al., 2003). The aim of this paper is to provide evidence on the determinants of diffusion of new drugs at the micro level.

As an example of prescription drug diffusion, this paper studies the case of statins, a type of cholesterol-lowering drugs. Treatment of heart disease has changed drastically over the past 30 years. A wide range of new treatments and forms of care for heart disease has been introduced, making this a prime area for the analysis of diffusion generally. Amongst these new treatments statins are of particular importance. The introduction of the first statin in the late 80s and early 90s offered new possibilities for the treatment of cholesterol and had a revolutionary impact on the treatment of coronary heart disease (CHD). Sales of statins doubled during the period 1991 to 1993 and prescription volume increased on average by 40% annually. Patients with cholesterol are at risk of developing atherosclerotic vascular disease. Its main manifestation is CHD followed by cerebrovascular disease (CVD) and periphereal vascular disease. Randomised controlled trials have shown the efficacy of statins in lowering cholesterol in primary and secondary prevention and they have also been shown to be cost-effective (NICE, 2006). We use prescription data from IMS Health to analyse the uptake of statins in the UK NHS primary care sector over the period 1991-2004.

The paper is organised as follows. Section 2 provides a description of the diffusion process with the aim of identifying the mechanism driving the demand for new pharmaceuticals. Section 3 describes the market for statins in the UK. Section 4 describes the data used in the empirical analysis. Section 5 presents the model and the econometric methods. Section 6 presents the results and the final section concludes.

2. What happens when a new drug enters the market? Determinants of the diffusion process.

Prior to entry into the market prescription drugs have been subject to a process of research and development in the pharmaceutical sector. We consider this phase as exogenous. The focus here is on the uptake of prescription drugs in the health care market, from an early stage during which there is little known about the characteristics of the drug and its performance in a non-trial environment to a phase in which the demand is well established and part of common practice.

In general, the uptake of new medical technologies is characterised by uncertainty. Usually this uncertainty has been linked to the early stage of adoption; however, this uncertainty may extend beyond initial adoption. New technologies are likely to suffer changes along their paths of diffusion. Incremental improvements will arise as a consequence of using these technologies in practice, and the degree of uncertainty will gradually decrease as users become more familiar with the technology. Hence, the process of diffusion should be considered as a dynamic process of learning characterised by informational flows that give users the information needed to convert availability into widespread adoption of the new drug.

There are different mechanisms in which such informational flows can operate. In economics, network externalities arise when the use of a good provides more value to the consumer the more consumers use the same technology. On the contrary, consumption externalities in the health care market are assumed to arise in terms of information (Berndt et al., 2003). Thus, the first mechanism is the information provided by consumption externalities arising from the demand of the new drug. Its diffusion over time will generate a stock of information that will be updated regularly. This information is available at the market level and comes as a signal of the acceptation of the entire market. The more the drug is prescribed the more information about the drugs functioning and effectiveness. The aggregation of the individual experience will convey information through consumption externalities. Here we refer to the doctor as the consumer and assume that the doctor acts as an agent for the patient. Whether the patient actually consumes the prescription drug, is compliant with the prescription advice, goes beyond the scope of the analysis and we treat this as exogenous.

The second mechanism through which information is gained is through the doctor's own experience. Drugs are experience goods: their demand will provide the consumer information about the quality and only through repeated prescription doctors will have a better understanding of the drug's attributes. The doctor will learn about the safety and efficacy of the drug through its own prescribing experience and the follow up of the patient. It is a process of "learning by prescribing". Furthermore, a doctor's clinical experience will be secured the more they prescribe the drug. Because of the heterogeneity of patients, drugs generally and statins specifically will have different effects on patients and this will broaden the learning process.

The experience obtained at both levels, by doctor's own prescribing experience and from the aggregated information available in the market, will reduce the degree of uncertainty. The more advanced the diffusion stage the lower the uncertainty. Moreover, this uncertainty may also be reduced in informal professional meetings happening regularly in the doctor's environment. The everyday interaction with peers is likely to be characterised by discussions that will increase their information. Hence, physician's professional networks may also be a key element influencing the valuation of the new drug.

Information gained through the publication of clinical trials will also aid this process. Evidence regarding the efficacy and safety available in randomised trials will help physicians to determine the cases for which the prescription of statins is appropriate. This evidence will facilitate the process of transforming the information available into clinical practice. The publication of the results from randomised-controlled trials provides evidence on the effect of using statins to lower cholesterol and reduce the incidence of coronary heart disease. National Service Frameworks in the area of heart disease and the assessment of statins by regulatory bodies such as NICE have also influenced diffusion rates.

During the process of gaining information about the drug, there are a number of other factors that may also affect the diffusion pattern. Doctors are part of a wider health care system, which through regulation provides incentives for a better use of the limited resources. Hence, the incentives provided individually to practices are likely

to determine the uptake of pharmaceuticals. For instance, financial incentives or treatment guidance provided by the main regulator might influence the prescription of newly available drugs and shape the demand for statins.

In this paper we integrate informational and organisational factors on the demand for new prescription drugs. Some recent studies have studied the diffusion of pharmaceuticals focusing on the role of consumption externalities, looking at the effect of the past sales on the market shares achieved by the manufacturer (Berndt et al, 2003). In such studies consumption externalities are analysed from an aggregated perspective. Consumption experience has also been analysed together with observable product characteristics (Currie and Park, 2002). We combine consumption externalities with the influence of experience goods as a mean of obtaining information and undertake analysis of the diffusion process at the micro level. The analysis also incorporates the influence of organisational factors.

3. Market for Statins in the UK

Statins are a class of drug within the lipid-lowering drugs. They are indicated for patients with cholesterol. High levels of cholesterol may cause atherosclerosis vascular disease. Statins have been proven to reduce all atherosclerotic cardiovascular disease events, and total mortality. They are recommended both as medical management for the prevention of cardiovascular events and as treatment for patients with history of cardiovascular disease.

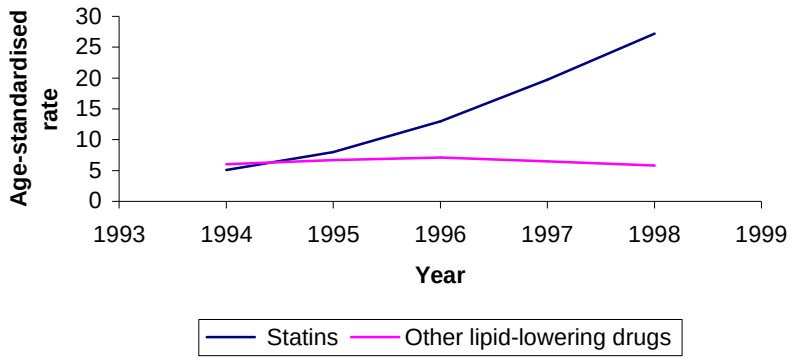
Coronary and cerebrovascular events are two of the diseases that account for the main burden of mortality and disability in the UK and they account for almost £5 billion in annual direct health care costs and cause 11% deaths and 19% in England and Wales, respectively (National Audit Office, 2005). Ischaemic heart disease and cerebrovascular disease are the first two leading causes of death not only in the UK but also worlwide.

During the early 80s fibrates were among the most common lipid-lowering drugs used to treat hiperlipidaemia. They were effective in controlling triglyceryds and HDL cholesterol. The introduction of the statins in the late 80s offered the possibility of treating patients with cholesterol with a drug highly effective in reducing LDL

cholesterol and total levels of cholesterol. Statins opened up a new line of treatment for cholesterol and showed to be more effective than other subcategories of serum lipid reducers in lowering LDL-cholesterol but less effective than the fibrates in reducing triglycerides. There has been a growth in the lipid lowering drugs category driven mainly by an increace in the utilisation of statins rather than a shift in the pattern of prescription from fibrates and other lipid lowring drugs to statins (Dickson and Jacobzone, 2003).

The evidence regarding statins is incontrovertible. Their effectiveness in reducing total and LDL-cholesterol have been extensively shown in the literature. Several clinical trials showed a positive effect of statins in lowering the onset of patients with high risk of coronary events and stroke in primary prevention. Moreover, in secondary prevention statins demonstrated to reduce cerebrovascular disease and cardiovascular events in patients in secondary prevention. Also, it has been shown that statins are cost-effective in lowering cholesterol. Overall, statins are well tolerated with no differences in safety (Maron et al., 2000; Palmer et al., 2003; NICE, 2006).

Figure 1. Persons prescribed drugs per 1000 patients: Statins and other lipid-lowering drugs

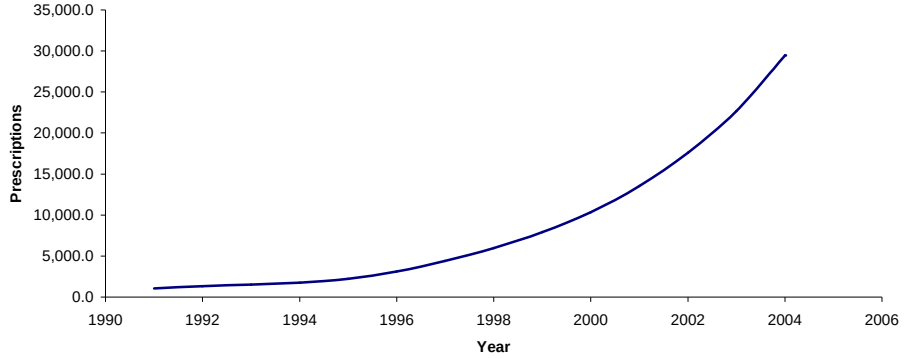


Source: Office for National Statistics. England and Wales
Note: Age standardised rate. 1994-1998

Figure 1 shows the trend in the rate of prescription of statins as compared to the rest of lipid lowering drugs in England and Wales. It can be seen that while the prescription of other lipid regulating drugs remained fairly stable over the period 1994-1998, the prescription of statins increased almost five-fold. These differences in trends are explained by the differences in the attributes between statins and the rest of

drugs in the serum lipid reducer category. Within this cateogry, fibrates are primarily aimed for the treatment of triglycerides and its use has been stable over the years. When comparing statins with the rest of lipid lowering drugs, statins are highly effective agents that have proved to give better results in the treatment for hypercholesterolaemia. Figure 2 shows the total number of prescription statins dispensed in the community in England from 1991 to 2004. There has been an increase in utilisation of statins as shown by the increase in the prescriptions dispensed. Both figures present the same increasing pattern in the demand for statins over time.

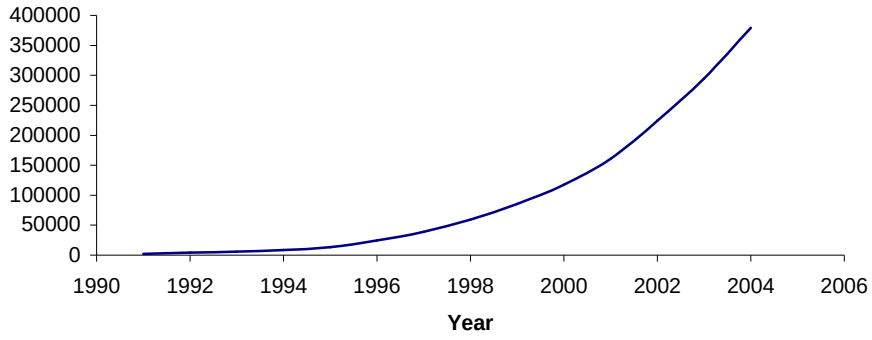
Figure 2. Total Number of Prescriptions Dispensed in the Community



Source: Prescription Cost Analysis, Prescription Pricing Authority.
Note: Total number of prescriptions (000's) dispensed in the community in England. 1991-2004

The first statin was marketed in the UK in 1989. However, data analysed for this study reveals that two years after the introduction into the health care market, the uptake of this particular prescription drug was not common practice. The source of data is IMS Health and provides all prescriptions of statins collected from a panel of over 130 practices within the primary care sector in the UK for the period 1991-2004. Figure 3 shows the number of prescriptions issued in the GP practices in the sample. There is a slow process of diffusion at the early stage while the uptake rate is accelerated over the later years. Similarly, the sample used for the analysis reproduce the increase in statin use showed at the national level as seen in figures 1 and 2. There is a shift to a faster diffusion in the years 1995 and 1996, which coincides with the publication of the first studies providing evidence on the effectiveness of statins in lowering cholesterol (Shepherd et al., 1995; Sacks et al., 1996).

Figure 3. In sample prescriptions



Source: IMS Disease Analyzer. IMS Health. 1991-2004.

We analyse the diffusion of statins as a therapeutic class and do not specify the submolecule that was prescribed. All statins have been showed to reduce levels of cholesterol and there are no differences in safety between them[1]. They were introduced sequentially over the 90s and the last statin, rosuvastatin, was introduced in 2003. Because they share the basic features and there are no significant differences, we assume there are inter-molecular spill-overs: once simvastatin (the first statin in the UK to be marketed) was introduced we would expect that the additional information that doctors need to learn is negligible as compared to the bulk of information that they need to learn for the first statin. In any case, by the time a new statin molecule is introduced, doctors may be still under the process of gaining knowledge on the efficacy and side effects of the statins already in the market. Thus, it is a process where there the incorporation of new molecules into the market takes part into the existing learning process.

4. Data

We use data from IMS Health, a commercial company that produces reports and collects data for the pharmaceutical sector. The data come from one of their databases (IMS Disease Analyzer) that contain prescription data from a sample of 130 practices throughout the UK covering three million patients. Prescription data is collected monthly at the practice level and it contains up-to-dated information. Quality and representativeness are checked on a regular basis. IMS Disease Analyzer tracks

[1] There is some limited evidence on differences in dosage. Certain brands market statins with high dosage levels with this in mind; however there is no evidence to assume that such a dosage effect is specific to a particular molecule.

doctors, patients and therapies over time and contains information on practice-specific characteristics, patient demographics and diagnostic and therapy information.

Each observation recorded in the IMS Disease Analyzer is a patient visit. The data analysed in this paper includes all visits in which there a statin was prescribed. A longitudinal database on the uptake of statins was constructed for the period 1991-2004. There is a short gap period between the introduction of the first statin and the first year of data collection, however it is a neglegible gap in data since the diffusion was at its very early stage[2]. Data in the sample indicates that even two years after the first statin was marketed, the demand for the new prescription drug was still at the very early stage of adoption. Similarly, the national data in the figures above also show that in the early 90s the diffusion was at its innovative stage. It was a process in which consumers were still in search of information and only few physicians were prescribing the drug.

5. Empirical specification

5.1. The model

In this study, we study the role of information and externalities together with the effect of organisational factors on the demand for pharmaceuticals. We consider a dynamic diffusion equation of the following form:

$$y_{it} = \alpha \cdot y_{it-1} + \beta \cdot x_{it} + \gamma \cdot d_{it} + \eta_i + u_{it}$$

where i and t index the practice where the prescriptions is issued and the year, respectively. The dependent variable y_{it} is the log of the per capita prescriptions in practice i at year t. x_{it} is a vector of that contains the explanatory variables and d_{it} is a vector of demographic controls. The specification also includes a practice-specific effect η_i to capture unobserved elements affecting the demand for pharmaceuticals and that are specific to the practice.

The data used in the paper records each office visit linked to the prescription of statins. Due to the data collection method, each prescription event is attached to a doctor's identifier; however, these identifiers do not necessarily identify the doctor

[2] IMS Disease Analyzer collection data started in 1991, it was only two years after the introduction in the UK market of the first statin, simvastain, and a year later than the second drug pravastatin was marketed.

that actually prescribes the statin and it is not possible to know exactly the number of statins prescribed by each doctor in the practice. Therefore, we cannot build a variable with the number of prescription issued by each doctor in the practice. Instead, we do know the practice where the prescription event took place and the number of doctors in the practice. Hence, the dependent variable is defined as the total number of prescriptions in the practice per year adjusted by the number of doctors in the practice. It is an average number of prescriptions per physician in each practice.

The lagged value of the dependent variable y_{it-1} captures the dynamics of the experience gained by the previous year prescription profile. This intends to capture the personal learning process from the repeated prescription of the experience good. The vector of independent variables includes two different sets of variables. In the first place we use sales in the pharmaceutical retail market (wholesaler and manufacturer distribution to retail pharmacy and dispensing doctors) provided by IMS Health. Sales are used as an indicator of the consumption externalities derived from the use of the drug in the market. A generalised use of the drug will provide consumers with a signal on the efficacy and side effects of the drug and this may convey information to the individual consumer.

Clinical evidence is also introduced in the specification in order to capture the information provided by randomised control trials in the use of the statins in primary and secondary prevention. There are three reference studies published in the mid-90s that are considered to give the first evidence of the effectiveness of statins: the Scandinavian Simvastatin Survival Study (4S) (Scandinavian Simvastatin Survival Study Group, 1994), the West of Scotland Coronary Prevention Study (WOSCOPS) (Shepherd et al., 1995) and Cholesterol and Recurrent Events (CARE) (Sacks et al., 1996). The clinical evidence variable indicates whether one, two or the three of these studies had been published at a specific point in time[3].

A second set of variables included in the analysis captures practice characteristics of the practice. The first is whether the practice joined the fundholding scheme in 1991

[3] There have been many studies looking at the effect of statins but rather than include them all, the variable is defined as to include only the three most important since they provided the first evidence of the high effectiveness of statins in reducing cholesterol.

(the year when the data started being collected). In the UK, between 1991 and 1999 practices could hold a budget for prescribing costs. It was shown that for the early waves of fundholders' there was a decrease in prescribing growth rates. Practices that were fundholders could provide different incentives on the demand for statins, especially during the early stage of the diffusion. The drawback of this variable is that it only reveals which practices were fundholders at the beginning of the data collection and this information was not updated later on. However, this captures the effect of this scheme during the innovating stage of diffusion. In 1999, all GPs were required to join into Primary Care Groups (PCGs) but this change we can be considered to happen in a mature stage where the efficacy of statins was better known.

The second practice characteristic relates to whether or not the practice is drug dispenser. This variable captures the opportunities given to the practice to generate additional income. Consequently, this might provide incentives to over prescribe. As in the case of fundholding, the information in this variable was recorded at the beginning of the collection period and was not updated but we would not expect many practices switching their dispensing status. The last practice characteristic variable contains the number of doctors in the practice. This variable is again related to the role of the information on the demand for prescribing drugs. The number of doctors in the practice may indicate the degree of interaction within the practice in sharing knowledge and experience on the prescription of statins. This variable can be thought of as the location where the information at both the personal and market level converge.

Finally, the specification also includes a vector of controls d_{it} for the health authority where the practice is located. It contains the percentage of the population over 65 as a control for the population that present higher risk of developing atherosclerosis disease. It also includes the number of GPs in the area to control for any shock that may alter the provision of primary health care in the area.

5.2. Panel data methods

In this section we discuss the estimation method of the model outlined above. We use autoregressive distributed lag models to estimate the specification above. The dynamic element is introduced here as a measure of the learning experience gained by past prescription experience. We consider the dynamic demand equation of the form:

$$y_{it} = \alpha \cdot y_{it-1} + \beta \cdot x_{it} + \eta_i + u_{it}$$

The model includes the lag of the dependent variable and independent explanatory variables. η_i denotes the unobservable cross-section specific effect and u_{it} is the disturbance term. The individual effects and the disturbances are assumed to be independently distributed and have the following structure:

$$E[\eta_i] = 0,\ E[u_{it}] = 0,\ E[u_{it}\eta_i] = 0 \text{ for } i = 1,...,N \text{ and } t = 2,...,T$$

and under the assumption of lack of serial correlation among the errors

$$E[u_{it}u_{is}] = 0 \text{ for } i = 1,...,N \text{ and } s \neq t$$

The OLS estimator of α will be inconsistent because the lagged value of the dependent variable is correlated with the error component and this will give an upward biased estimator. By first-differencing the equations, the unobserved effect is eliminated. Applying OLS to the transformed equation gives the Within Group estimator. However, the first difference will introduce correlation between the transformed lagged dependent variable and the transformed error term and the estimator will be downward biased (see Bond (2000) for an extended discussion).

The above assumptions on the error component imply the following moment restrictions:

$$E[y_{t-s}\Delta u_{it}] = 0 \text{ for } t = 2,...,T \text{ and } s \geq 2$$

These conditions are exploited in the first-differenced generalised method of moments (GMM) developed in Arellano and Bond (1991). The exact form of the matrix of instruments will depend on the assumptions on the explanatory variables x_{it} and the elements of the error component. There will be different extra moment condition depending on whether x_{it} is assumed to be endogenous, predetermined or strictly exogenous.

In addition to the moment conditions for the first-differenced equations, there are some extra conditions as possible instruments for the level equations.

$$E[u_{it}\Delta y_{it-1}] = 0 \quad \text{for} \quad t = 3,...,T$$

$$E[u_{it}\Delta x_{it-1}] = 0 \quad \text{for} \quad t = 3,...,T$$

This method was first proposed by Arellano and Bover (1995) and further developed by Blundell and Bond (1998). These conditions applied to the level equations together with the moment conditions for the first-differenced equations give the so-called system GMM estimator. Monte Carlo simulations in Blundell and Bond (1998) suggest that this estimator is more robust than first-differenced estimators to the presence of weak instruments when the series are highly persistent. The estimator has been found to have poor finite sample properties when the lagged levels are weakly correlated with the first differences. Using additional assumptions available in the system GMM can improve and have superior finite sample properties.

6. Results

In this section, the results of the estimation are presented. Before we explain the results, note that some of the variables included in the specification are time-constant (fundholding, drug dispensing and the number of doctors in the practice) and hence the first-difference GMM method will drop them. Since they are relevant to the purpose of the analysis, they are included in the model as an interaction with time and they will capture the effect of the variable together with the time trend.

Table 1 presents the results. The first column of the table reports the coefficients of the OLS. As expected the OLS estimate of the lagged dependent variable is upward biased since it does not take into account the correlation between the lag and the error term. The second column gives the Within Group estimates. The first differences of the Within Group introduce correlation between the difference in the lag and the difference in error. Both the OLS and Within Group estimates are inconsistent in a dynamic model.

Table 1. Dynamic equations						
	OLS	**Within**	**DIFF-GMM**	**SYS-GMM**	**DIFF-GMM Endog**	**SYS-GMM Endog**
y_{it-1}	0.7627545	0.5587928	0.5023637	0.5969222	0.6118121	0.5793095
	(0.0115524)	(0.0160953)	(0.0500453)	(0.0475306)	(0.0396463)	(0.0383766)
Sales	0.1766177	0.3929485	0.4338733	0.3886055	0.4096254	0.4199726
	(0.020537)	(0.0308209)	(0.0770485)	(0.0678745)	(0.07987)	(0.0556696)
Clinical Evidence	0.0904274	0.1188414	0.1272584	0.105036	0.1275827	0.1033718
	(0.0147602)	(0.0145355)	(0.0200862)	(0.0183369)	(0.0187964)	(0.0183456)
Fundholding	-0.0000106	-0.0056184	-0.0052298	-0.0000115	-0.0025853	-0.0000116
	(0.0000097)	(0.0049653)	(0.0121866)	(0.0000197)	(0.0112544)	(0.0000205)
Drug dispenser	2.62E-05	0.0062151	0.0179815	0.0000461	0.0161356	0.0000479
	(0.0000121)	(0.0061594)	(0.0131412)	(0.0000268)	(0.0121915)	(0.0000275)
# Doctors	-9.75E-06	0.0010606	0.0020371	-0.0000156	0.0039964	-0.0000161
	(0.00000228)	(0.0010857)	(0.0026824)	(0.00000515)	(0.0024452)	(0.0000052)
GPs	-0.0000232	0.0003613	0.0005161	-0.0000359	0.0007982	-0.0000369
	(0.0000118)	(0.0001098)	(0.0001732)	(0.0000241)	(0.000174)	(0.0000249)
Pop over 65	0.0025824	0.0067189	0.0494487	0.000186	-0.0238559	-0.0002671
	(0.0060123)	(0.033082)	(0.0755573)	(0.0121571)	(0.0666267)	(0.0127461)
m1			-3.01	-3.59	-3.51	-3.49
m2			-1.89	-2.04	-2.12	-2
Hansen			0.398	0.317	0.999	1

Notes: Standard errors in parentheses
m1 and m2 are the first and second order serial correlation tests
P-value reported for the Hansen test
GMM results are one-step robust estimates

The third column reports the results for the one-step first-differenced GMM estimator. The coefficient is positive and significant. This supports the hypothesis that the personal learning process through the prescription experience in the previous year is an important factor of the demand for pharmaceuticals in the current period. The prescription pattern will be highly determined by the previous period prescription profile. The Hansen test has a p-value that fails to reject the null hypothesis that the instruments satisfy the orthogonality conditions.

In autoregressive-distributed lagged models, the correlation between the lagged levels and the first difference is weak when the parameter of the lagged dependent variable is close to one. Then, the series are highly persistent and the lags used as instruments for the first-differences become weak instruments. Table 2 presents the AR(1) model estimates for the OLS, Within Groups and GMM estimates. In all cases, the prescription series are highly persistent and they don't have an exact unit root. GMM estimators have a similar coefficient and the differenced GMM estimator is not highly

biased. As Blundell and Bond (1998) show, in the presence of high persistent series there are additional moment conditions for the level equations that will improve the estimation.

Table 2. AR(1) specifications

	OLS	Within Group	GMM-DIF t-2	GMM-SYS t-2
y_{it-1}	0.902	0.894	0.937	0.944
	(0.005)	(0.006)	(0.007)	(0.007)
m1	-7.78	-8.74	-2.89	-3.84
m2	-2.97	-3.37	-2.64	-3.03
Hansen			0.004	0.054

Notes: Standard errors in parenthesis
m1 and m2 are the first and second order serial correlation tests

The fourth column presents the estimates of the system GMM. Again, the Hansen test of overidentifying restrictions has a p-value that fails to reject the null hypothesis. Hence the additional moments restrictions exploited for the equations in levels improve the estimation of the coefficient. The presence of first-order autocorrelation cannot be discarded; however we fail to reject the null hypothesis of no second-order autocorrelation at the 1% level of significance. The presence of first-order autocorrelation does not affect consistency of the estimates since this relies on the lack of second-order autocorrelation.

The fifth and sixth columns report the first-differenced and system GMM estimates considering the variable sales as endogenous. The assumption that sales are strictly exogenous is relaxed and we assume that sales are potentially correlated with the error term. Misspecification is tested and suggests that sales are better modelled as endogenous. Sales have the expected sign and a positive effect on the demand for new drugs. The positive sign of the sales estimate supports the fact that informational externalities at the market level will have a positive influence on the prescription as doctors will have a signal of the efficacy of the drug. Moreover, clinical evidence published in scientific journals is also shown to have a positive effect on demand and proves to be a reliable source of information to doctors.

The negative sign of the coefficient on the fundholding variable shows a negative impact of managing a budget in the prescription of new drugs especially in the innovative stage of the diffusion when the information available is scarce. Drug dispensing has a positive effect on demand, and this shows that extra opportunities on getting some extra income may enhance the prescription of new drugs. Finally, the number of doctors in the practice has a negative sign on the number of prescriptions. Note that there is a change in sign when we use the system GMM method to adjust for the presence of persistent series. This could be interpreted as the effect of the interaction with peers having a weak effect on the prescription behaviour. While it can be important at early stages of diffusion, the importance of the effect of the number of doctors diminishes quickly over time and it reaches the point where its effects is negligible.

Table 2. Dynamic equations: current and past sales

	OLS	Within	GMM DIFF	GMM SYS
y_{it-1}	0.7747254	0.5734534	0.6350219	0.6125821
	(0.0116467)	(0.0165962)	(0.040229)	(0.0419914)
Sales t	0.6126373	0.6298853	0.6226948	0.6213811
	(0.0809613)	(0.0755669)	(0.1143797)	(0.1051929)
Sales (t-1)	-0.4030472	-0.2492003	-0.3844925	-0.2201938
	(0.0724366)	(0.0726193)	(0.1098637)	(0.1002278)
Clinical Evidence	0.0292814	0.0831819	0.0640625	0.0684482
	(0.0182934)	(0.0178251)	(0.0254436)	(0.0248021)
Fundholding	-0.0000109	-0.0045601	-0.0025678	-0.0000117
	(0.00000961)	(0.0049569)	(0.0110476)	(0.0000189)
Drug dispenser	0.0000249	0.0074463	0.0153948	0.000044
	(0.000012)	(0.0061475)	(0.0121621)	(0.0000252)
# Doctors	-9.34E-06	0.001777	0.0036559	-0.0000149
	(0.00000226)	(0.0011017)	(0.002397)	(0.00000485)
GPs	-0.0000206	0.0004386	0.0005943	-0.0000326
	(0.0000117)	(0.0001117)	(0.000157)	(0.000023)
Pop over 65	0.0026043	0.0052437	-0.0667666	0.0000262
	(0.0059571)	(0.0329649)	(0.0667974)	(0.0117946)
m1			-3.64	-3.64
m2			-1.49	-1.63
Hansen			0.9	1

Notes: Standard errors in parentheses
m1 and m2 are the first and second order serial correlation tests
P-value reported for the Hansen test
GMM results are one-step robust estimates

We consider now the case of including the current and past sales into the model instead of considering the effects of consumption externalities only captured by the level of current sales. The inclusion of the past sales would introduce a dynamic element capturing the cumulative effect of the consumption externalities as opposed to the case of including only current sales that would provide only the latest information available. The specification now has the following form:

$$y_{it} = \alpha y_{it-1} + \beta \cdot Sales_t + \delta \cdot Sales_{t-1} + \delta \cdot x_{it} + \eta_i + u_{it}$$

where x_{it} includes the rest of explanatory variables and demographic controls. The results are similar to those in Table 1. The third and fourth columns present the results for the first-differenced and system GMM. It reinforces the key role of the informational externalities through the information available in the market and suggests that the accumulation of information from the previous period have a considerable impact on the demand for the new drug over the diffusion process. Hence, both current and past sales help to shape physicians' perceptions of the effectives of the new drug.

Table 3. Dynamic equations: GMM SYS

y_{it-1}	0.5789607	0.6121398
	(0.0385072)	(0.0421146)
Sales t	0.4210348	0.6210993
	(0.0558497)	(0.10515)
Sales (t-1)		-0.218916
		(0.1001814)
Clinical evidence	0.1032529	0.0685383
	(0.0183663)	(0.0248759)
# Doctors	-0.0000166	-0.0000154
	(0.00000537)	(0.000005)
GPs	-0.0000363	-0.0000322
	(0.0000239)	(0.0000221)
Pop over 65	-0.0040548	-0.0033839
	(0.0126347)	(0.0117314)
m1	-3.49	-3.64
m2	-2	-1.63
Hansen	1	1

Notes: Standard errors below estimates
m1 and m2 are the first and second order serial correlation tests
P-value reported for the Hansen test
GMM results are one-step robust estimates

Table 3 presents the results for the dynamic demand equation when the organisational factors reflecting whether the practice is fundholder or drug dispenser are not included in the specification. The first column refers to the equation that accounts only for the current sales and the second column presents the results for the model that includes current and past sales. In both cases the Hansen test of overidentifying restrictions has a p-value that fails to reject the null hypothesis of the validity of the orthogonality conditions. We fail to reject the null hypothesis of second-order autocorrelation at the 1% level of significance. The estimate for the lagged dependent variable is again showing the importance of the experience gained as indicated by the past prescription behaviour. Consumption externalities are shown to have a positive impact on the demand for new drugs and clinical evidence provides a formal source of information on which doctors rely. Results in table 3 thus suggest that the demand for new pharmaceuticals is mainly driven by informational factors at two levels: the first coming from the consumption externalities derived from the market as a whole and the second from the personal experience acquired by past prescription.

7. Conclusions

This is one of the first studies to analyse diffusion of prescription drugs at a micro level. We use prescription data to analyse the uptake of new drugs within the UK NHS primary care sector. The diffusion process is inherently dynamic: informational flows provide the consumers with the evidence on the effectiveness of the drug. It is a learning process where doctors receive information from different sources. We use dynamic panel data methods to capture these elements. We find that consumption externalities and experience gained through prescription are the main factors driving the demand for drugs after they are first marketed in the health care sector. In addition, the evidence provided in scientific journals on the functioning of the drug plays a role in the uptake and physicians use this evidence as a formal source of information.

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