Adoption of Prescribing Innovations in Irish General Practices

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Abstract

The contribution of innovations to economic growth is only realised when an innovation is widely used and diffused. Drawing on the equilibrium and disequilibrium models of timing of adoption, the influence of practice heterogeneity (rank effects), strategic behaviour (stock and order effects) and learning and knowledge spillovers (epidemic effects) on the decision-making of adopting innovations in General Practices is examined. Our analysis is concerned with the first adoption of a prescribing innovation and the factors influencing GPs' decision-making regarding prescribing a new drug for the first time. This paper specifically examines the adoption of six prescription drugs by a sample of Irish GPs (625) over a 54 month period.

In line with the literature, we find that early adopters of one drug are not early adopters of all drugs. Using duration analysis the following question is addressed: what is the probability of a GP prescribing a specific drug very shortly after a certain time, given that the GP has not prescribed it by that time? A decrease in time to adoption is reported for practices with a nurse and practices with a secretary. An increase in time to adoption is reported for older GPs and rural practices. A decrease in time to adoption is strongly evident for GPs who prescribe from larger portfolios and for GPs who are first-movers in at least one of the other drugs examined.

Introduction

The aim of this paper is to explain the timing and intensity of adoption of innovations in General Practices in Ireland. The influence of individual unit heterogeneity (rank effects), strategic behaviour (stock and order effects) and learning and knowledge spillovers (epidemic effects) on the perceived benefits of adopting innovations in General Practices is examined. Choosing a medicine for a patient is a fundamental activity of doctors (Prosser, Almond, and Walley 2009; Thistlehwaite, Ajjawi, and Aslani 2010). This paper examines the first adoption of new prescription drugs and the factors influencing GPs' decision-making regarding such innovations. In line with previous studies, a prescribing innovation is the prescribing of a new drug for the first time (Jones, Greenfield, and Bradley 2001; Rogers 2003).

Our analysis is one of the first studies examining the determinants of adoption of new prescription drugs in General Practice to employ Duration Analysis, which will determine what factors impact on the probability of a GP prescribing a new drug very shortly after a certain time, given that the GP has not prescribed it by that time. The General Medical Services (GMS) Prescribing Database contains data on the number of prescriptions written by a sample of approximately 600 GPs for the period from October 1999 to March 2004. Our analysis focuses on six drugs which were brought to the Irish market during the sample period, and were adopted over the 54 month time-period by a large proportion of the GPs in the sample.

Theoretical Models of Timing of Adoption

The word 'diffusion' is commonly used to describe the spread of new ideas, products and processes throughout a market, population or social system (Schumpeter 1942; Hall 2004; Rogers 2003). Diffusion is the cumulative or aggregate result of a series of individual decisions that weigh the incremental benefits of adopting an innovation against the costs of change. This paper examines the individual decision-making concerning adoption of prescribing innovations. There is a substantial body of literature investigating the timing of adoption of new technologies and the factors influencing the decision-making concerning the timing of first-adoption. A GP is considered to have adopted a drug if he/she prescribes a drug on at least one occasion to at least one patient.

The main theoretical approaches to the timing of adoption include a disequilibrium model of diffusion which takes account of epidemic and learning effects and an equilibrium model of diffusion associated with organisation characteristics and strategic interaction. The epidemic models regard diffusion as resulting from the spread of information, and assume that (i) a potential user will adopt a new technology upon learning of its existence and (ii) information on the existence of the technology is spread by direct contact between a potential user and user (Baptista 1999). A key aspect of the structure of the epidemic models is that there is an end level of use for the new technology, and the diffusion path is the disequilibrium approach to that end point (Stoneman 1987).

Rogers (2003), considered the pioneer of diffusion of innovations theory, examines diffusion and the adoption of innovation through the lens of epidemic and learning effects. Rogers (2003) defines diffusion as the process by which (1) an innovation (2) is communicated through certain channels (3) over time (4) among the members of a social system. Rogers (2003) states that an innovation is an idea, practice or object that is perceived as new by an individual or other unit of adoption. In brief, epidemic theories of diffusion assume information asymmetries between different potential adopters. The basic hypothesis of the simple epidemic model is that non-adopters are more likely to innovate, the more of the other members of their social system have adopted.

Alternative theoretical approaches to the subject of diffusion use an equilibrium framework, and assume that information in the economy is perfect. These equilibrium models of diffusion concentrate on the decision-making process of individual units as the epidemic models do, but assume that knowledge about the characteristics, benefits and costs of the new technology is widespread. Differences in adoption timing occur because potential adopters differ from each other and due to strategic behaviour of individual units.

In equilibrium models of diffusion an individual or a unit's decision to adopt depends upon the gains from adoption relative to the cost of adoption. As these gains change over time, so too does the number of adopters. Three influences on adoption are generally identified: rank, order and stock effects. *Rank (or probit) effects* result from the assumption that potential adopters of a technology have different inherent characteristics and therefore obtain different returns from the use of new technology, i.e. individual units' heterogeneity is

the driver of adoption. These different results generate different preferred adoption rates (Karshenas and Stoneman 1993).

Stock effects models consider that as the number of users of a new technology increases, the benefits from adoption declines. Therefore, at a certain point in time, the number of accumulated adopters makes adoption by the remaining units not profitable. *Order effects models* argue that an individual unit's position in the adoption order determines its return from the use of the technology, that is, individual units higher in the adoption order obtaining greater returns than units lower in that order. Therefore, if an individual unit expects the number of future adopters to be high, it will decide to adopt earlier (Karshenas and Stoneman 1993).

Many authors examining the timing of adoption view the equilibrium and disequilibrium models of diffusion as complementary approaches (Karshenas and Stoneman, 1993; Battisti et al, 2007). This study will construct an encompassing model reflecting the different strands in the timing of adoption literature - rank, stock, order and epidemic effects- and will let the data indicate if these effects are empirically relevant to the timing of GPs adoption of prescription drugs.

Determinants of Adoption of Prescription Drugs

To date empirical studies have focused on the learning effects and practice/physician characteristics in examining adoption of new prescription drugs. Dybdahl, Andersen, Sondergaard, Kragstrup and Kristiansen (2004), in a study of Danish GPs, test the hypoethesis that physicians' early adoption of new drugs is a personal trait independent of drug groups. Dybdahl *et al.* (2004) report that early adoption of one type of drugs is not associated with early adoption of another. In fact, in an examination of GPs' adoption of new drugs and previous prescribing of drugs belonging to the same therapeutic class, Dybdahl, Andersen, Sondergaard, Kragstrup and Kristiansen (2005) find no consistent association between GPs' level of drug prescribing and their adoption of new drugs of the same therapeutic group. Steffensen *et al* (1999) report that their data indicates that adoption of new drugs is dependant on both physician and drug characteristics. These findings are in contrast to earlier adoption studies which stress the importance of physician characteristics (Coleman, Katz, and Menzel 1966).

Kozyrskyj, Raymond, and Racher (2007) conducted a study on newly marketed drugs in Canada to determine if early prescribers had different socio-demographic and professional characteristics compared to majority and late prescribers. In two of the four drugs examined, Kozyrskyj *et al* (2007) found that early prescribers of those drugs were more likely than the majority and late adopters to be hospital affiliated. Adoption times for new drugs is shorter for partnership than single-handed practices (Steffensen, Toft Sorensen, and Olesen 1999). A possible explanation for this finding is that the larger the number of patients in a practice, the more likely the GP is to see a patient who might be a candidate for a new drug (Dybdahl et al. 2004). This finding is in line with an earlier study, which found group practitioners adopt new drugs significantly faster than solo practitioners (Williamson 1975). However Williamson (1975) puts forward a different explanation for this finding, hypothesising that the longer a doctor spends in discussion with his/her doctor colleagues, the faster he/she is likely to adopt a new drug.

Tamblyn, McLeod, Hanley, Girard and Hurley (2003) examined the initial utilisation rate of new prescription drugs among physicians in Quebec and the physician and practice characteristics associated with early use. This study found lower utilisation rates of new drugs among physicians with a rural or remote practice location. Tamblyn *et al.* (2003) also report lower utilisation rates of new drugs among physicians with a high proportion of elderly patients in their practice, compared to higher utilisation rates for larger practices (practice volume). Male physicians' are more likely to prescribe a new drug than female physicians (Tamblyn et al. 2003).

Prosser, Almond, and Walley (2009) conducted a qualitative study in the north-west of England, examining the factors that influence GPs' uptake of new drugs. As expected Prosser *et al.* (2009) report that most prescribing decisions are multi-factorial, with the most frequently cited biomedical influences being the failure of current therapy and an adverse effect profile of alternative medicines. Hospital consultants were the second most cited reason for prescribing a new drug, followed by patient requests third.

The above literature highlights the impact physician, practice and drug characteristics have on physicians' decisions to adopt new drugs.

Sources of Data

GMS Prescribing Database

The GMS Payments Board provides reimbursement services to primary care contractors for the provision of health services to GMS patients in their own community. GMS patients are public patients who are entitled to attend GPs free of charge and also receive prescription medicines free of charge. The GMS Prescribing Database contains patient-level data for prescriptions filled in the Health Service Executive (HSE) South, South-East and North-East for the period October 1999 to March 2004.

When a GMS patient gets a prescription from a GP, they fill it either in a pharmacy or, if their GP has a dispensing licence, at the GP practice. The medicine is dispensed free of charge to the patient and a duplicate of the prescription is sent by the dispenser to the GMS (Payments) Board for payment. A number of details are entered into the prescribing database, including GP identifiers, dispenser identifiers, drug details which follow the anatomical therapeutic chemical (ATC) classification system, and quantity prescribed. As this dataset relates to payment of dispensers, it is of good quality hard data. The GMS prescribing database provides monthly data for the period October 1999 to March 2004. The prescription level observations in each monthly file ranged from 600,000 to 1,000,000.

The patient-level database was restructured to provide data on the percentage of GPs prescribing each of the 1,137 drugs over the 54 month time-frame. In general each drug follows one of three patterns – a relatively constant proportion of GPs prescribing it, an increase in the proportion of GPs prescribing it or a decrease in the proportion of GPs prescribing it. Almost 70% of the 1,137 drugs are prescribed by a similar proportion of GPs over the 4½ year time-frame. The level of adoption of the 214 drugs (approx. 18%) increased over the time period, with the level of adoption of 134 drugs (approx 18%) decreasing over the same time period. In our analysis, we are concerned with identifying the factors that impact on the timing of GPs' decisions to adopt a new prescription drug. In order to do this, it was decided to choose a small sample of drugs that would form the basis for the in-depth econometric analysis.

The drugs identified for further analysis include drugs brought to the Irish market during the time-period, which saw a significant proportion of GPs prescribing them over the

54 month period. This allows us analyse the factors impacting on the timing of adoption of a new drug for a large proportion of the GPs in the sample. The following six drugs were chosen representing drugs prescribed that operate on different physiological organs or systems: *esctialopram,* an antidepressant; *esmoprazole*, a proton pump inhibitor, *rofecoxib*, an anti-inflammatory; *desloratadine*, an antihistamine; nicotine chewing gum; and *drospirenone & ethinylestradiol*, a hormonal contraceptive. As some GPs in the sample may have an interest in a certain area or in certain conditions, a sample of drugs operating on different organs and systems eliminates the potential for inter-relationships between adoption patterns.

Figure 1: Proportion of GPs adopting Six Drugs

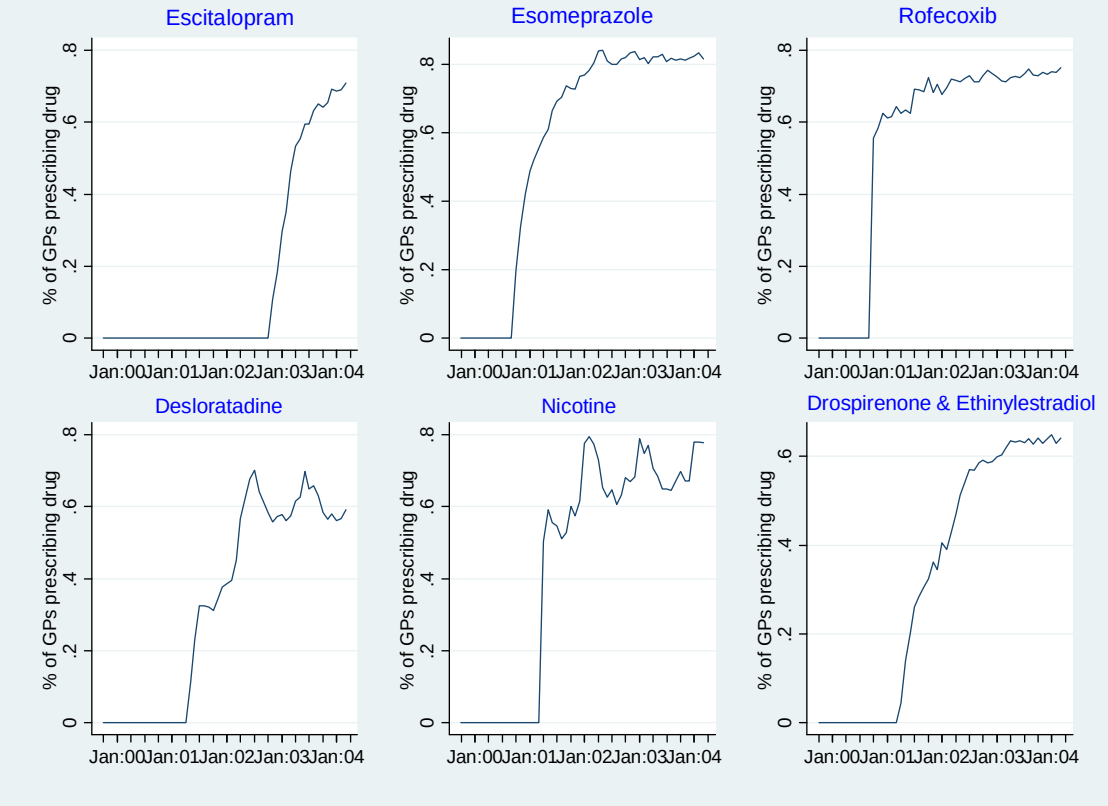

Figure1 presents the proportion of GPs prescribing these six drugs over the 54 month time-period. To elucidate, the top-left graph illustrates that no GPs prescribed *esctialopram* until the latter half of 2002, from the time of first adoption levels of adoption increased strongly and by March 2004 (the last month of the time-period) the level of adoption was approximately 70%. Similar shaped diffusion curves are presented for *esmoprazole*, *rofecoxib* and *drospirenone & ethinylestradiol,* where the proportion of GPs prescribing the drugs increased steadily until a significant proportion of GPs were prescribing the drug at the end of

the time-period. As expected with an antihistamine drug, *desloratadine* is prescribed by more GPs at certain times of the year, with up to 70% of GPs prescribing it during the summer months, and less GPs prescribing it during the remaining months. The diffusion curve for *nicotine* presents a seasonal pattern as well, with more GPs prescribing this drug at the beginning of the calendar year.

GP Characteristics Database

In 2001, GP & practice characteristics were obtained through primary data collection from 625 GPs in the HSE South, South-East and North-East. This sample of GPs comprises almost a quarter of the GP population in Ireland, and provides this study with time-invariant GP characteristic variables. Further explanatory variables such as portfolio breadth, stock and order effects were constructed from the GMS Prescribing Database. Descriptive statistics for these explanatory variables are presented in Table 1 and discussed in detail below.

Rank Effects

Nurse, Secretary, Dispensing Practice, GP Age, Drugtarget60 & Drugtarget50

As presented in Table 1, 58% and 79% of GPs surveyed worked in a practice with a nurse and secretary respectively. 12% of GPs surveyed worked in a dispensing practice. The average age of GPs in this sample is 49 years, with a minimum age of 30 years and a maximum age of 72 years. The drug target variables relate to the Indicative Drug Treatment Scheme. The scheme provides for the calculation of monetary prescribing targets for each GMS scheme GP, taking into consideration the make-up of his/her patient panel with regard to the age and sex of the patients. The scheme is voluntary and GPs retain the right and obligation to prescribe as they consider necessary. Savings are encouraged through the form of incentives, and there are no sanctions in place for those who fail to meet their target. In the panel dataset, the Indicative Drug Treatment Scheme variable is represented by two separate dummy variables. The first, *drugtarget60,* takes a value of one for GPs with prescribing costs less than 95% of the national age related average costs and who qualify for 60% of any savings made due to meeting targets. The second dummy variable, *drugtarget50,* takes a value of one for GPs who qualified for 50% of any savings made due to meeting targets and a value of 0 otherwise.

Table 1: Descriptive Statistics of Explanatory Variables

Variable Names	Mean	St. Dev.	Min	Max
Rank Effects				
Practice Nurse *Practice with a Nurse*	0.58	0.49	0	1
Practice Secretary *Practice with a secretary*	0.79	0.41	0	1
Dispensing Practice *Practice dispenses medicine*	0.12	0.32	0	1
GP Age *GP age in years*	49yrs	8.3 yrs	30yrs	72yrs
Drug Target 60 *GPs receive 60% of savings made from meeting prescribing targets*	0.37	0.48	0	1
Drug Target 50 *GPs receive 50% of savings made from meeting prescribing targets*	0.24	0.42	0	1
Epidemic Effects				
Portfolio *% of drugs prescribed by GP out of portfolio of drugs prescribed by all GPs*	0.25	0.098	0.001	0.45
Rural Practice Allowance *GPs receive an allowance if practice is in a low population area*	0.12	0.32	0	1
Order & Stock Effects				
Order Effects *First mover (first 6 months of adoption) in at least 1 of 6 drugs*	0.35	0.48	0	1
Stock Effect n06ab10 *% of adopters of escitalopram*	0.38	0.30	0	0.74
Stock Effect a02bc04 *% of adopters of esomeprazole*	0.19	0.30	0	0.78
Stock Effect m01ah02 *% of adopters of rofecoxib*	0.59	0.31	0	0.84
Stock Effect r06ax27 *% of adopters of desloratadine*	0.50	0.34	0	0.88
Stock Effect n07ba01 *% of adopters of nicotine*	0.58	0.29	0	0.82
Stock Effect *% of adopters of drospirenone & ethinylestradiol*	0.59	0.30	0	0.79

N = 625 GPs

Epidemic Learning Effects

Rural Practice Allowance & Portfolio Breadth

GPs are entitled to a rural practice allowance if they live and practice in an area with a population of less than 500 people. As is evident from Table 1, 12% of GPs in this sample are in receipt of a rural practice allowance. The p*ortfolio breadth1* variable was constructed to capture the range of drugs prescribed by each GP as a percentage of the total number of drugs being prescribed by all GPs. Given that all the time-invariant variables are from 2001, it was decided to construct this variable from the June 2001 data. In June 2001, a total of 874 different drugs were prescribed by GPs, with GPs on average prescribing 25% of these drugs, as presented in Table 1. The maximum percentage of these drugs prescribed by any one GP was 45%. This variable is included as an epidemic learning effect, as it is surmised that GPs who prescribe from a larger portfolio of drugs have had the benefit of learning from these adoption decisions.

Stock & Order Effects

The order effect dummy variable captures whether a GP was a first mover in at least one of the six drugs being examined, i.e. whether a GP prescribed the drug in the first six months of it being prescribed. 35% of GPs prescribed at least one of the six drugs in the first 6 months of its' adoption. For example, in this sample *n06ab10* was first prescribed in November 2002. Therefore, the order variable takes a value of one for GPs who prescribed *n06ab10* between November 2002 and April 2003 inclusive. Similarly, the order variable takes a value of one for GPs who prescribe any of the six drugs in the first six months of their adoption. The order variable takes a value of zero if a GP does not prescribe any of the six drugs in the first six months of their adoption.

A stock effect variable was constructed for each of the 6 drugs, which represents the percentage of GPs who have adopted the drug. This variable allows us to determine if the perceived benefits from adopting a new drug decline, as the number of previous adopters increases. This variable is time-variant, so the descriptive statistics in Table 1 should be read bearing this in mind. Suffice to say all 6 drugs indicate minimum adoption percentages of zero and maximum adoption percentages of greater than 70.

Methodology

The aim of this empirical exercise is to explain the timing of the adoption of prescription drugs by GPs in Ireland, and the econometric technique employed to do so is Duration Analysis. The pertinent question being addressed is: what is the probability of a GP prescribing a specific drug very shortly after a certain time, given that the GP has not prescribed it by that time?

Our analysis is one of the first studies examining the determinants of adoption of new prescription drugs in General Practice to have employed Duration Analysis, an approach which has strengths in relation to several of the shortcomings of conventional bivariate or aggregate diffusion approaches (Burton *et al*, 2004; Jones *et al*, 2007). It is well established in the diffusion literature that the adoption of an innovation involves the accumulation of information, and the act of adoption will be conditioned by more than the economic and social circumstances that exist at the time of adoption, but the accumulation of experience over the prior period (Burton *et al*, 2004; Hall 2004; Rogers 2003)). Consequently, the use of duration models is superior to conventional bivariate techniques that analyse adoption at a point in time and are not able to capture the intertemporal nature of adoption (Burton *et al*, 2004).

The purpose of Duration Analysis is to statistically identify those factors which have a significant effect on the length of a spell, and therefore, in Duration Analysis, the dependent variable measures the time elapsed before an event occurs (Jones *et al*, 2007). In our analysis, the dependent variables measure the time elapsed before a drug is prescribed by a GP. In other words, we are defining the length of a spell for a GP in the sample as the realisation of a continuous random variable, T, that has the following cumulative distribution function or failure function:

$$F(t) = P(T \leq t). \qquad \text{(Eqn.1)}$$

For example, the Accelerated Failure Time (AFT) model assumes a linear relationship between the log of (latent) survival time T and characteristics X:

$$ln\ (T) = \beta^{*\prime}X + z \qquad \text{(Eqn.2)}$$

where β* is a vector of parameters and z is an error term.

The probability distribution of duration can be specified by the Weibull, exponential, log-logistic and log-normal (as demonstrated in Eqn. 2) distributions. It is necessary to carry out specification tests to determine which of these distributions best fits the failure time regressions for the six drugs. In line with Baptista (2000), Greene (2000) and Kiefer (1988) specification testing of the failure time models in this study includes an examination of *pseudo-residuals*, or generalised residuals, log-likelihood scores and Akaike's Information Criterion (AIC). These specification tests demonstrated that of the Weibull, exponential, log-logistic and log-normal distributions, the log-logistic distribution was a better specification for five of the six failure time regressions and the log-normal distribution for one of the failure time regressions. Therefore, the failure times models discussed below are specified by the log-logistic distribution for drugs – *esctialopram (n06ab10)*, *esmoprazole (a02bc04)*, *rofecoxib (m01ah02)*, *desloratadine (r06ax27), nicotine* (*n07ba01)*- and the log-normal distribution for *drospirenone & ethinylestradiol (g03aa12)*. For ease of presentation, the econometric results are presented in relation to the seven digit ATC codes for each drug. The ATC classification system divides drugs into different groups according to the organ or system on which they act and their chemical, pharmacological and therapeutic properties

Econometric Results

A duration, or failure time model, is used to explain time to adoption as a function of the independent variables. Initially, a baseline model with all the explanatory variables included was examined. A number of specification experiments were conducted where non-linear effects, interaction effects and splitting variables are incorporated into the baseline model. Given the results from theses regressions, the preferred models for all six drugs initially included all explanatory variables and the breadth-squared variable in failure time models for *m01ah02* and *n07ba01*, given the non-linear relationship identified between time to adoption of these two drugs and portfolio size. However, in a ‘stepwise’ fashion, variables with z-statistics of less than |0.5| were excluded from the relevant failure time models. The regression results are presented in Table 2 and discussed below. When interpreting the results of an AFT model, a negative coefficient means a negative effect on duration and, therefore, a positive effect on adoption speed (Baptista, 2000).

Table 2: Time to Adoption (Oct 1999 –Mar 2004) – Marginal Effects

	n06ab10	**a02bc04**	**m01ah02**	**r06ax27**	**n07ba01**	**g03aa12**
	mfx/se	mfx/se	mfx/se	mfx/se	mfx/se	mfx/se
Rank Effects						
Practice Nurse	-0.611***	-5.320***	-1.638			-0.810**
	(0.145)	(1.945)	(1.174)			(0.332)
Practice Secretary	-0.238	-5.765***	-0.781	-1.767**		-0.846*
	(0.182)	(2.075)	(1.273)	(0.692)		(0.435)
GP Age	0.034***		-0.112*	0.060*	0.171**	0.058***
	(0.009)		(0.062)	(0.031)	(0.077)	(0.020)
Drug Target 50	-0.097	1.743	-1.06	-1.487**	3.429**	-0.399
	(0.135)	(1.702)	(1.186)	(0.587)	(1.708)	(0.342)
Drug Target 60		-3.262	-2.45	-1.411**	3.213	-0.561
		(2.370)	(1.539)	(0.665)	(1.974)	(0.385)
Dispensing Practice		2.169	-3.329*	-0.68	-2.336	1.007*
		(3.195)	(1.988)	(0.825)	(2.158)	(0.530)
Epidemic Learning Effects						
Rural Practice Allowance	0.423**	1.832	2.277	1.168	-1.518	1.316**
	(0.193)	(3.226)	(2.034)	(0.856)	(2.322)	(0.543)
Portfolio Breadth	-4.671***	-84.066***	-101.810***	-23.718***	-142.399***	-8.404***
	(0.750)	(14.385)	(20.308)	(4.744)	(26.956)	(1.886)
Portfolio Breadth2			100.116**		162.577***	
			(42.731)		(52.522)	
Order & Stock Effects						
Order Effects	-3.029***	-19.020***	-12.677***	-7.145***	-18.964***	-3.129***
	(0.208)	(2.327)	(1.514)	(1.081)	(3.233)	(0.512)
Stock Effects	8.006***					
	(0.383)					
Stock Effects		-30.156***				
		(10.376)				
Stock Effects			-14.874**			
			(6.489)			
Stock Effects				-11.533**		
				(5.691)		
Stock Effects					-53.544***	
					(12.587)	
Stock Effects						14.426***
						(1.740)
N	23366	8595	8150	13628	10871	15082
chi2	516.205	820.051	749.085	249.483	807.954	187.403
bic	-1407.6	-315.94	-433.23	-263.98	-1340.8	204.142

Rank Effects

In relation to GP practices with a nurse, time to adoption decreases for three of the drugs examined. This finding is statistically significant at the 1% level for drugs *n06ab10* and *a02bc04* and statistically significant at the 5% level for drug *g03aa12*. Similarly, a decrease in time to adoption is reported for practices with a secretary in three of the six drugs examined. This finding is statistically significant at the 1% level for drug *a02bc04*, at the 5% level for drug *r06ax27*, and at the 1% level for drug *g03aa12*. These findings are in line with much of the literature which report firm size and human capital impacting positively on adoption of innovations (Karshenas and Stoneman 1993; Baptista, 2000).

In relation to the age of the GP, in general time to adoption increases as age increases. This relationship is found to be statistically significant for four of the drugs - *n06ab10, m01ah02, r06ax27* and *g03aa12.* However, it should be noted that a decrease in time to adoption as age increases is reported for drug *r06ax27*. Masters (2008), following a systematic review of the literature, reports similar findings in relation to doctors and internet adoption, with adoption being greater among younger doctors. Meade et al (2009) in a study examining the factors affecting the use of electronic patient records by Irish GPs report greater adoption of EPR by younger GPs. However, not all small business adoption studies report significant findings in relation to age, Burton et al (2003) report no statistically significant relationship between age of a farmer and the adoption of organic horticultural technology.

Results in relation to the dispensing practice variable are generally insignificant, and the two significant results are inconclusive, with time to adoption increasing for GP practices that dispense prescriptions for drug *g03aa12* and time to adoption decreasing for GP practices that dispense prescriptions for drug *m01ah02*. The drug target variables, which measure the percentage of savings received by the practice made by meeting prescribing targets, in general produce insignificant results, and the statistically significant results reported are inconclusive indicating a decrease in time to adoption for drug *r06ax27* and an increase in time to adoption for drug *n07ba01*.

Epidemic Learning Effects

An increase in time to adoption is reported for practices in receipt of a rural practice allowance for two of the drugs examined. This finding is statically significant at the 5% level for drug *g03aa12* and the 10% level for drug *n06ab10*. Tamblyn *et al.* (2003) found lower utilisation rates of new drugs among physicians with a rural or remote practice location. Coleman *et al.* (1966) report in the classic drug diffusion study where physicians' decisions to prescribe a new antibiotic tetracycline were investigated that early adopters attend more out-of-town medical meetings that late adopters. While similar data is not available for this study, it is fair to suggest that GPs with practices in receipt of a rural practice allowance are less likely to be able to attend meetings and conferences than urban based GPs. Similarly, it is likely that such practices are visited less frequently by drug company representatives, which prove an important source of information for GPs in relation to prescribing decisions (Jones, Greenfield, and Bradley 2001).

A very strong relationship is found in relation to time to adoption and breadth of portfolio. Across all six drugs and statically significant at the 1% level, time to adoption decreases for GPs who prescribe drugs from larger portfolios. As discussed in the previous section, this relationship between portfolio size and time to adoption of two of the drugs is non-linear in two of the drugs examined, indicating a u-shaped relationship between portfolio breadth and time to adoption. It is also possible that our portfolio breadth variable could also be considered a proxy for practice size, as the more patients a GP sees the more likely they require a larger portfolio of drugs to prescribe from. Previous studies have reported higher utilisation rates of new drugs for larger practices, as measured by practice volume (Tamblyn *et al.* (2003).

Order & Stock Effects

A strong relationship is also reported in relation to time to adoption and order effects. Time to adoption decreases for GPs who prescribe at least one of the six drugs in the first six months of its adoption decrease. This result is reported across all six drugs and is statically significant at the 1% level. The stock effects variables results are less conclusive than the order effects variable results. However, in four of the drugs (*a02bc04*, *m01ah02*, *r06ax27* and

n07ba0) as the percentage of adopters of the drug increases, time to adoption decreases. However, it should be noted that for the remaining drugs (*n06ab10* and *g03aa12*) time to adoption increases as the percentage of previous adopters increases.

These particular results present a conflicting picture. Order effects models argue that the firm's position in the adoption order determines its return from the use of the technology, that is, firms higher in the adoption order obtaining greater returns than firms lower in that order. Therefore, if a firm expects the number of future adopters to be high, it will decide to adopt earlier (Karshenas and Stoneman 1993). There appears to be clear evidence of order effects in the drug adoption decision-making of GPs as presented in Table 2. Stock effects models consider that as the number of users of a new technology increases, the benefits from adoption declines. Therefore, at a certain point in time, the number of accumulated adopters makes adoption by the remaining firms not profitable (Karshenas and Stoneman 1993). The inverse of this relationship is reported in this study, as the number of previous adopters increases, time to adoption decreases. This result indicates that as the number of adopters of each drug increases, the benefits from adoption do not decline. Baptista (2000) explains how the accumulation of adopters should have a negative effect on the adoption rate because of the stock effect. However, the epidemic effect acts through a learning-by-contact process, and consequently the stock of previous adopters will also bring forth a positive effect on adoption. It is possible that such an effect will counteract the expected stock and order effects, making the net effect of the variable ambiguous. If learning effects are strong enough to compensate for stock effects, then a positive net effect of the stock of previous adopters should be found (Baptista 2000). Given the conflicting results in relation to the stock effect on time to adoption of the six drugs, it is possible that the stock effect variable is capturing a learning effect, and that in four of the six drugs this learning effect is decreasing time to adoption but in relation to the remaining two drugs this learning effect is increasing time to adoption. These learning effects may be specific to these particular drugs.

Discussion

This paper highlights the rapid adoption by Irish GPs of six prescription drugs following their availability on the Irish market. Being an early prescriber of one drug does predict early adoption of some drugs, however it is not a strong predictor of being an early adopter of all drugs examined. For instance, no GP in the sample adopted all six drugs within

the first six months of them being adopted by their peers. This finding contradicts the image of early adopters as being related to a general innovative predisposition. Therefore, it appears that a GPs decision to prescribe is heavily dependent on the new drugs in question (Dybdahl *et al*. 2005; Steffensen *et al.* 1999).

In general, this study does not find that certain factors impact on the decision to prescribe all drugs examined, however, a number of patterns or commonalties are reported. Older GPs operating from practices without the assistance of a nurse and secretary are less likely to prescribe new drugs soon after they reach the marketplace. Also, GPs in receipt of the rural practice allowance are also less likely to be early prescribers of new drugs. However, two explanatory variables impact on the decision to prescribe all six new drugs examined. The first of these variables portfolio breadth indicates that the larger the portfolio of drugs a GP prescribes from the more likely they are to quickly prescribe a new drug to the market. Similarly, GPs who prescribe at least one of the new drugs examined in the first six months of its' adoption by the sample of GPs, the more likely they are to prescribe another new drug to the market. While the order effects variable was created to capture whether GPs prescribing decisions are made from a strategic viewpoint, it is possible that this variable is also capturing an epidemic learning effect. Both the portfolio breadth variable and the order effects variables strongly influence the decision to prescribe each of the six drugs examined.

A common concept put forward in the literature is how new drugs diffuse into general practice is a two-step model with hospital consultants as the innovators and GPs as the followers. In other words, it is the consultant who initially prescribes the new drug and GPs repeat prescribe these drugs when the patient returns to the primary care setting. Florentinus' (2006) study of the adoption of new drugs in a Danish primary care setting contradicts the expected two-step model. Florentinus (2006), while acknowledging the influence of medical specialists in GPs' prescribing decisions, finds that GPs themselves are responsible for a considerable amount of all early prescriptions for new drugs. In fact, for a substantial group of GPs specialist endorsement is not even a requisite to initiate new drug prescribing at all (Florentinus, 2006). Given data restrictions, this study is not able to control for the potential influence of hospital consultants on the prescribing decisions examined. However, of the six drugs examined, the antihistamine, the smoking cessation medication and the hormonal contraceptive are unlikely to be repeat prescriptions following an initial prescription by a hospital consultant. It is likely that the proton pump inhibitor and the anti-inflammatory

prescribing decisions may be influenced by hospital consultants initial prescribing decisions, and the antidepressant to a lesser extent.

This study has important implications for policy makers in terms of influencing the prescribing of new drugs. It is clear that older GPs and GPs practicing without the assistance of a nurse or secretary, in general, are slower to adopt new drugs. Therefore, any attempt to influence adoption of new drugs needs to focus on these GPs. Likewise, learning effects, capturing by the rural practice allowance, portfolio breadth and order effects variables, influence GPs decisions to prescribe new drugs. It is clear that the ability to obtain information on new drugs from a location and an experience point of view is an important factor in these prescribing decisions. Pharmaceutical companies, to a large extent, and Continuing Medical Education (CME) meetings provide information in relation to new drugs to the market. However, if policymakers want to influence the uptake of new drugs, whether new compounds to the market or generics of existing compounds, additional means of conveying information to remote GPs and GPs who do not prescribe from a large portfolio of drugs need to be considered. Such considerations are of particular importance in terms of reducing health care spending.

New drugs are approved on the basis of clinical trials of usually limited duration on a relatively small numbers of patients. The limitations to this clinical testing system result in insufficient data in relation to the effects of long-term exposure, the frequency of rare adverse effects, the effects in special populations or for indications not studied before marketing, and the efficacy of a new drug relative to others for the same indications. These uncertainties advocate restraint in prescribing new drugs during the early post-marketing period (Florentinus 2006). For instance, *rofecoxib* was first licensed in Ireland on the 12th November 1999. By March 2004, almost three-quarters of GPs in the sample were prescribing *rofecoxib* to patients. Merck & Co Inc., who produced *rofecoxib* under the brand names Voixx and Ceoxx, voluntarily recalled the drug on September 30, 2004, amidst evidence that it drastically increased users's risk of heart attack and stroke. Therefore, findings from this study should also be helpful in the development of targeted educational strategies to promote the appropriate use of newly marketed drugs.

Conclusion

In line with the literature, this study finds that early adopters of one drug are not early adopters of all drugs. However, a number of patterns or commonalties in the adoption of six new prescription drugs to the Irish market by a sample of 625 GPs are reported. We find practice heterogeneity (rank effects) and location and prescribing experience (order & epidemic effects) impact on the adoption of new drugs by Irish GPs. It is clear that adoption of new prescription drugs is not uniform across all GPs. Therefore, policymakers need to be aware of the impact these factors have on the diffusion of drugs in the Irish primary health care system.

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