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## Doctors' fees in Ireland following the change in reimbursement: Did they jump?

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David Madden, University College Dublin

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**UCD SCHOOL OF ECONOMICS  
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# Doctors' Fees in Ireland Following the Change in Reimbursement: Did They Jump?

David Madden (University College Dublin)

November 2005

**Abstract:** This paper analyses the pure time-series properties of doctors' fees in Ireland to assess whether a structural change in the series is observed at the time of the change in reimbursement in 1989. Such a break would be consistent with doctors responding to the reimbursement change in a manner predicted by supplier-induced-demand behaviour and would provide indirect evidence that such inducement had taken place. Structural change is assessed on the basis of CUSUM and CUSUMSQ tests. The data is also analysed for the presence of unusually influential observations. In neither case are the results consistent with a break around the time of the introduction of the change.

**Key Words:** Reimbursement, influential, structural change

**JEL Code:** I11, C22, C52.

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# **Doctors' Fees in Ireland Following the Change in Reimbursement: Did They Jump or Were They Pushed?**

## **1. Introduction**

In a recent paper Madden, Nolan and Nolan (2004, henceforth MNN) explored the extent to which visiting patterns to General Practitioners in Ireland changed following a change in reimbursement. More specifically, in Ireland, individuals below an income threshold, termed “medical card patients”, are entitled to free GP consultations while the remainder of the population, termed “private patients”, must pay the full cost of each consultation. Prior to 1989, GPs were reimbursed on a fee-per-service basis for both medical card and private patients, by the State and the patient respectively. In part in response to evidence in favour of demand inducement presented by Tussing (1983, 1985), the reimbursement system for medical card patients was changed from fee-for-service to capitation in 1989, thus removing any incentive for GPs to induce visits from medical-card patients. MNN examined the “difference-in-differences” between medical card and non-medical card visits before and after the change in reimbursement. The results showed that the differential in visiting rates between medical-card holders and others did not narrow, as might have been anticipated if supplier induced demand played a major role.

One factor which MNN were unable to take account of was whether, following the change in reimbursement, GPs increased their fees for private patients to offset any loss in induced demand from medical-card patients. Failure to take account of this implies that some form of supplier-induced demand for medical card patients prior to 1989 cannot be unambiguously ruled out. This is because while the change in reimbursement was introduced with the intention of lowering medical-card patients'

visits (and evidence suggests that it succeeded in this in the short-run at least), doctors may have responded to their loss of income from this form of inducement by raising fees for non-medical card patients. If GP visits for non-medical patients are price inelastic, as is typically assumed, then such a course of action would have led to increased revenue from private patients, yet no narrowing of the visiting differential since visits from *both* groups would have fallen.

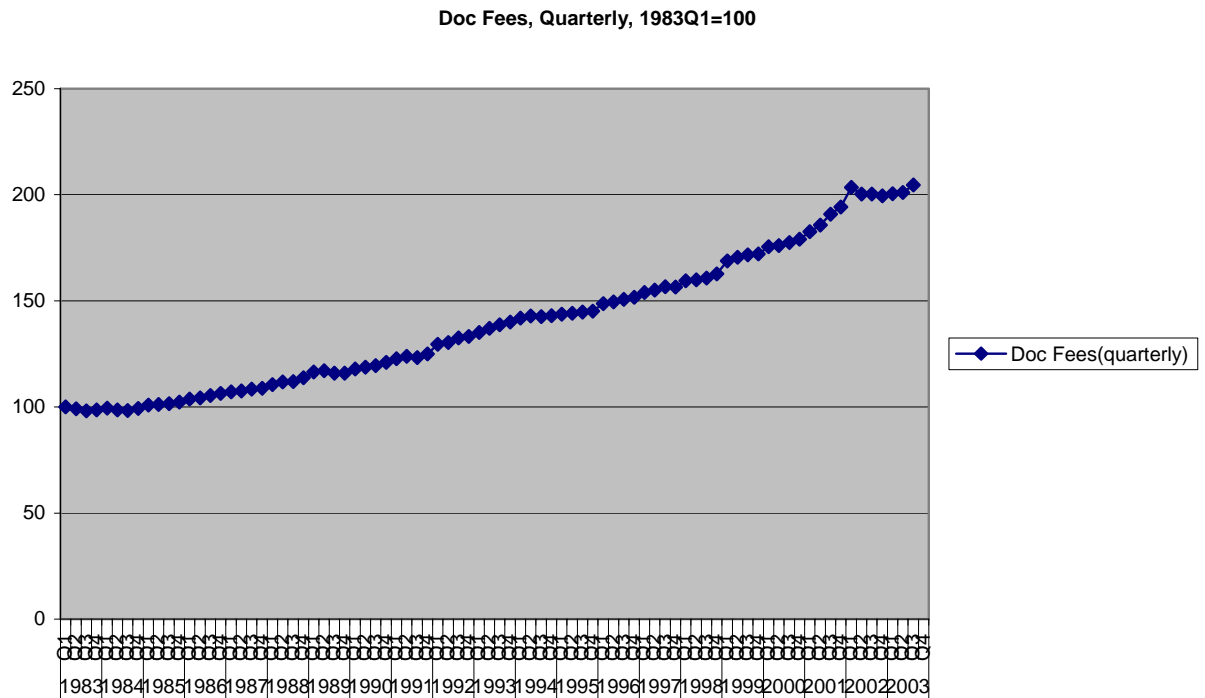
Unfortunately MNN were unable to explicitly control for such an effect since their data listed GP visits on an *annual* basis (i.e. numbers per year for each individual) and so it was not possible to assign individual visits to the particular month or quarter. In the absence of sufficient time variation it was not possible to condition on price in the analysis.

In this note we utilise an alternative data source and approach to investigate the evolution of doctors' fees over time. In particular, we examine whether any form of break or discontinuity (we define precisely what we mean by this below) can be observed in the time-series data on doctors fees around the time the change in reimbursement was introduced. If such a break is observed then it is consistent with doctors responding to the change in reimbursement by raising private patients' fees. In turn this could be regarded as a classic reaction to a situation where inducement had previously existed, but where the scope for such inducement had been diminished by the change in reimbursement.

The remainder of the paper is organised as follows. In the next section we describe our data source and the methodology we employ to detect any break in the time-series on doctors' fees. In section 3 we present our results and in section 4 we offer concluding comments.

## 2. Data and Methodology

This section describes our data and methodology. The data we use is quarterly data on doctors' fees from 1983 Q1 to 2003 Q3 provided by the Irish Central Statistics Office. This index is a sub-component of the overall Consumer Price Index. To obtain the change in the real price of doctors' fees we deflate the index for doctors' fees by the index for all items. The graph below shows the change in the real price of doctors' fees from 1983 to 2003 (indexed at 100 for 1983 Q1).



Purely eye-balling the graph we see that doctors' fees (in real terms) stayed constant from early 1983 to about the last quarter of 1985. We then see the index start to increase and there is some evidence of a slight "blip" upwards in the first quarter of 1989, but this seems to be followed by a levelling off for the rest of 1989. From then on the rate of increase is reasonably constant (though there is some evidence that it

picks up around the end of 2000) with evidence of other occasional blips e.g. 1992 Q1, 1999 Q1 and, in particular, 2002 Q1. The fact that most of the blips occur in Q1 may indicate some seasonality in price setting (i.e. GPs change their fees at the beginning of every year) and the particularly large rise in 2002 Q1 may reflect the changeover to the euro.<sup>1</sup> We return to this below.

While eye-balling the data can be revealing in terms of suggesting possible breaks, it is also desirable to test for such breaks more formally. The approach we take first of all relies less on identifying structural breaks rather than detecting unusually influential observations. First we introduce some necessary notation. This involves concepts and measures which are familiar in regression analysis except that here they are applied to individual observations as opposed to the regression as a whole.

Suppose we have an estimated regression model of the form  $y = Xb + e$  where  $y$  is a  $n \times 1$  vector,  $X$  is an  $n \times k$  matrix and  $b$  is a  $k \times 1$  vector of estimated coefficients with  $e$  the vector of residuals. Thus we have  $n$  observations and  $k$  independent variables (including the intercept, if any).  $x_j$  represents the  $j$ th observation,  $y_j$  is the observed value of the dependent variable with predicted value  $\hat{y}_j = x_j b$ . The residuals are defined as  $\hat{e}_j = y_j - \hat{y}_j$  and  $s^2$  is the mean square error of the regression. We also write  $V = s^2 (X'X)^{-1}$ .

We define a diagonal element of the projection matrix,  $h_j$ , as  $h_j = x_j (X'X)^{-1} x_j'$ . The standard error of the prediction for observation  $j$  is defined as  $s_{p_j} = \sqrt{x_j V x_j'}$  which can also be expressed as  $s_{p_j} = s \sqrt{h_j}$ . The standard error of the

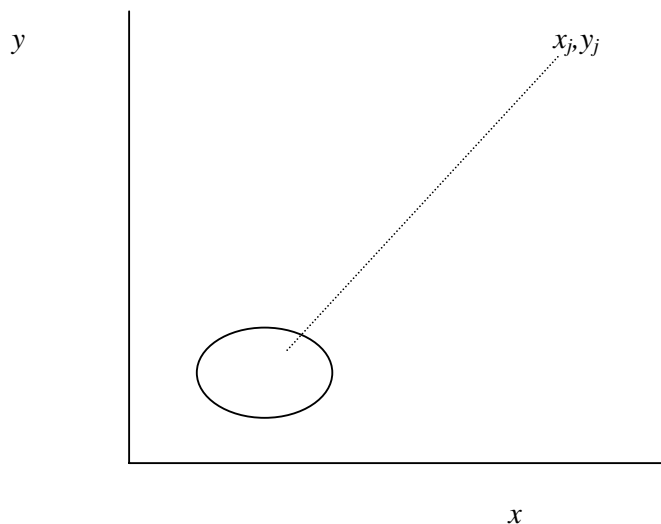
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<sup>1</sup> In January 2002 Ireland, along with a number of other nations in the EU, adopted the euro as its currency. This led to many prices being “rounded” up or down. A rounding up of doctors’ fees seems to be a plausible explanation for the relatively sharp rise observed in 2002 Q1.

forecast is defined as  $s_{f_j} = s\sqrt{1+h_j}$  while the standard error of the residual is  $s_{r_j} = s\sqrt{1-h_j}$ . Standardised residuals are defined as  $\hat{e}_{s_j} = \hat{e}_j / s_{r_j}$  while studentised residuals are  $r_j = \frac{\hat{e}_j}{s_{(j)}\sqrt{1-h_j}}$ . In the latter expression  $s_{(j)}$  represents the root mean square error with the  $j$ th observation removed. We are now in a position to explain the various statistics used to detect unusually influential observations.

Following the discussion in Belsley, Kuh and Welsch (1980) we can think in terms of three key issues in identifying model sensitivity to individual observations. These are residuals, leverage and influence. Taking residuals first, each individual residual  $\hat{e}_j = y_j - \hat{y}_j$  tells us how much the fitted value of the dependent variable differs from the observed value. Any given data point  $(x_j, y_j)$  with a large residual is an outlier and clearly there is concern that such outliers will exert undue influence upon estimated coefficients.

However, large residuals are not the only way in which individual points can affect estimates unduly. In the same way that  $y_j$  and  $\hat{y}_j$  can be far apart it is also possible that some individual  $x_j$  may be far apart from the mass of other  $x$ 's.





Suppose we have a scatterplot of  $y$  against  $x$  such that all points are located in a mass concentrated in the ellipse in the lower left side of the diagram, apart from a single point  $(x_j, y_j)$  in the top right-hand corner. The dashed line shows the estimated regression line obtained, which clearly comes very close to the point  $(x_j, y_j)$ . Thus  $(x_j, y_j)$  is not an outlier in the sense of having a large residual, yet it has a dramatic effect on the estimated slope of the regression line, since if this point was deleted then the estimates would change markedly. The point  $(x_j, y_j)$  is said to have high *leverage* and it would be reflected in a high value of  $h_j$ .

Thus we can think of influence being exerted in two ways, via large residuals or a high degree of leverage. We now introduce a number of statistics which can combine both notions and give us some idea of the degree of influence of each observation. The different statistics will reflect different types of influence e.g. with regard to the estimated coefficient  $b$ , or perhaps the standard error of  $b$ .

The first measures we will examine, apart from the plot of residuals, will be the measures of leverage,  $h_j$ , and the standardised and studentised residuals defined earlier. From the expression above it is clear that the standardised errors are simply the residuals adjusted for their standard errors. Standardised residuals adjust using the root mean square error while studentised errors adjust using the root mean square error of a regression omitting the observation in question. Belsley, Kuh and Welsch (1980) state that studentised residuals can be interpreted as the  $t$  statistic for testing the significance of a dummy variable equal to 1 in the observation in question and 0 elsewhere, since such a variable would effectively absorb the observation and so remove its influence upon determining the other coefficients in the model.

A very direct measure of the influence of a single observation is provided by the DFBETA statistic. This measure focuses on one particular regression coefficient and measures the difference between that coefficient when the  $j$ th observation is included and excluded, with the difference being scaled by the estimated standard error of the coefficient. Belsley, Kuh and Welsch (1980) suggest a critical value of  $|DFBETA_j| > 2/\sqrt{n}$ , while it is also common practice to simply use 1 i.e. the observation shifted the estimate by one standard error.

The next three statistics are attempts to create an index which is affected by the size of the residuals and the degree of leverage and as they are related we will deal with them together. The first of these is the DFITS measure (Welsch and Kuh, 1977)

which is defined as  $DFITS_j = r_j \sqrt{\frac{h_j}{1-h_j}}$  where  $r_j$  are the studentised residuals. Thus

large values of the residuals will increase the DFITS measure as will large values of  $h_j$ . Intuitively, DFITS is a measure of the difference between predicted values for the  $j$ th case when the regression is estimated with and without the  $j$ th observation.

Following from the DFITS measure we have Cook's Distance (Cook, 1977)

which is defined as  $D_j = \frac{1}{k} \frac{s_{(j)}^2}{s^2} DFITS_j^2$  with  $k$  the number of independent variables,

including the constant,  $s$  the root mean square error of the regression and  $s_{(j)}$  the root mean square error when the  $j$ th observation is omitted. Thus Cook's Distance is a measure of the difference between the coefficient vectors when the  $j$ th observation is omitted.

Welsch's Distance (Welsch, 1982) is defined as  $W_j = DFITS_j \sqrt{\frac{n-1}{1-h_j}}$  where

$n$  is the total number of observations. Thus Welsch's Distance involves another normalisation by leverage apart from that already embodied in the DFITS measure.

Belsley, Kuh and Welsch (1980) suggest a critical value of DFITS of  $2\sqrt{k/n}$ , suggesting threshold values of Cook's and Welsch's Distance of  $4/n$  and  $3\sqrt{k}$  respectively.

The final statistic we consider addresses the influence of individual observations on the variance-covariance matrix of the estimates. The measure is the ratio of the determinants of the covariance matrix with and without the  $j$ th observation with a

formula  $COVRATIO_j = \frac{1}{1-h_j} \left( \frac{n-k-\hat{e}_{s_j}^2}{n-k-1} \right)^k$  where  $e_{s_j}$  is the standardised residual.

Belsley, Kuh and Welsch (1980) suggest a critical value of  $|COVRATIO_j - 1| \geq \frac{3k}{n}$ .

An alternative approach to searching for unusually influential observations is to examine the data for a structural shift in the estimated relationship. Perhaps the best known of such tests is the Chow test. Suppose we have an idea of where the structural shift takes place. The model is then estimated before and after the supposed structural shift and an F test can then be carried out on whether the estimated relationship is the "same" before and after the supposed shift. Suppose there are  $n_1$  observations before the structural shift and  $n_2$  observations following the structural shift. Let  $S_1$  represent the residual sum of squares for the regression estimated on all the observations and let  $S_2$  and  $S_3$  represent the residual sum of squares for the regression run on the  $n_1$  and  $n_2$  observations respectively. Then if there are  $k$  parameters to be estimated the statistic

$$F = \frac{(S_1 - S_2 - S_3)/k}{(S_2 + S_3)/(n_1 + n_2 - 2k)}$$

follows an F distribution with degrees of freedom  $(k, n_1+n_2-2k)$ .

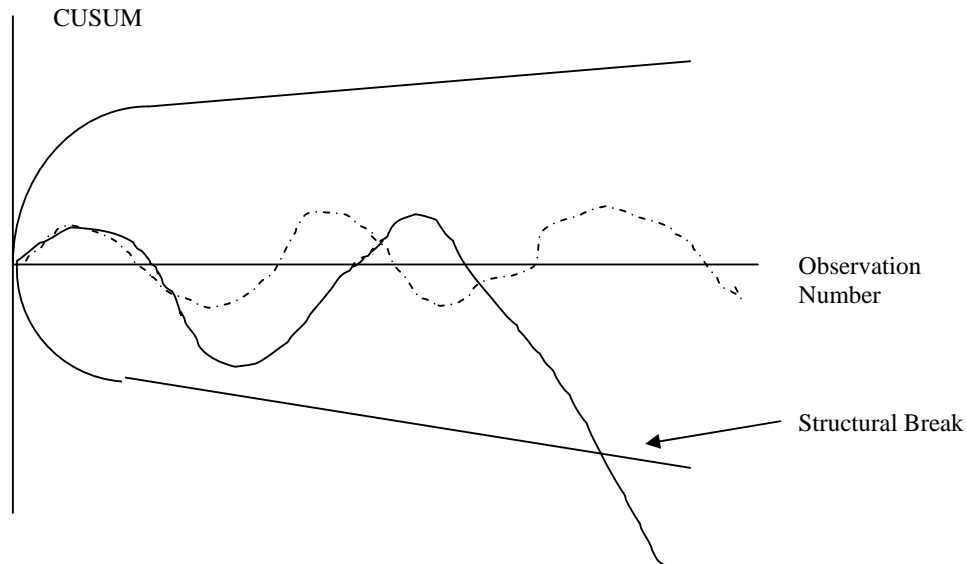
As we will see below however, a problem with the Chow test is that while it can tell whether the relationship has changed for two different periods with the cut-off date chosen arbitrarily, it does not identify when exactly the relationship begins to change.

A potentially more useful approach is to examine the *recursive residuals* from the regression (see Brown et al., 1975, and Galpin and Hawkins, 1980). These residuals are not unlike the studentised residuals mentioned above. Suppose our data consists of  $n$  observations. Then discard the last data point and estimate the model using the first  $n-1$  observations. We can denote vector of estimated coefficients as  $b_{n-1}$ . The recursive residual, denoted by  $w_{n-1}$  is then defined as the standardised residual of the last observation from the new line, being standardised by the variance  $\sigma^2$ . The procedure can then be carried out for the second last point as well and the regression fitted to the first  $n-2$  points giving  $w_{n-2}$ . By continually omitting points in this way  $n-p$  recursive residuals can be calculated, assuming we are trying to estimate  $p$  parameters.

The examination of plots of the recursive residuals can be extremely useful in detecting a “change in regime” in the regression model. As Brown et al. (1975) point out “...the recursive residuals seem preferable [to other transformations of least-squares residuals] for detecting the change of a model over time since until a change takes place the recursive residuals behave exactly as on the null hypothesis” (Brown et al., 1975, p. 150). Brown et al. suggest plotting the cumulative sums (CUSUM) of

the recursive residuals, defined by  $z_i = \sum_{j=1}^i \frac{w_j}{\sigma}$ , where  $i$  can take on values from 1 to

$n-p$ . If all the regression assumptions are satisfied then the plot of  $z_i$  should be a random walk within a parabolic envelope (where the borders of the envelope can reflect significance levels) about the origin since the expectation of these recursive residuals is zero.



When a structural break occurs, we typically observe a secular increase (or decrease) in  $z_i$ . In the illustration above we show recursive residuals for two regressions, with the dashed line showing no signs of a structural break, while the constant line shows clear signs.

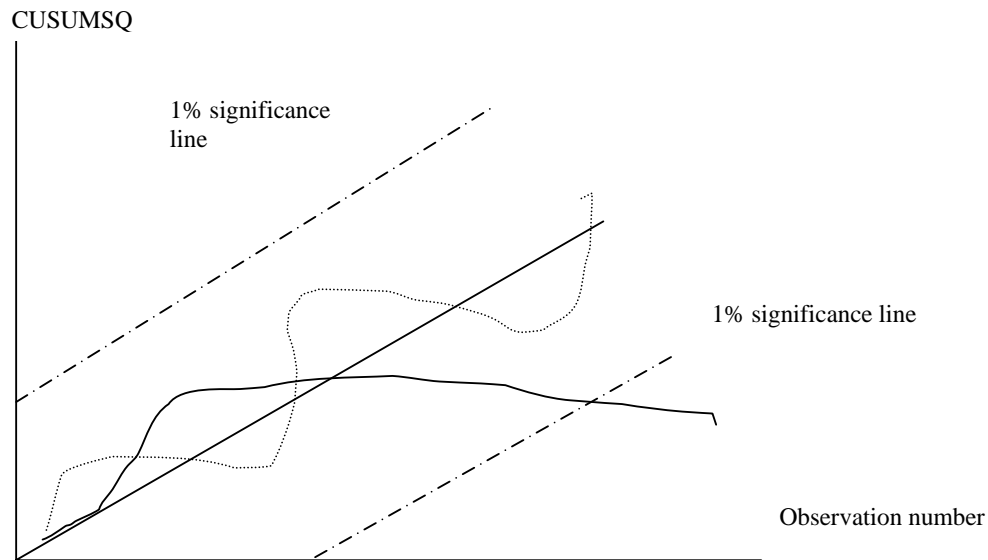
Complementary to the CUSUM plot is that of the CUSUM of squares. This

plots the quantities  $\frac{\sum_{i=p+1}^r w_i^2}{\sum_{i=p+1}^n w_i^2}$ ,  $i=p+1, p+2, \dots, n$ . Brown et al. claim that this plot is

particularly useful when departures from constancy of the  $b_i$  is “...haphazard rather than systematic” (Brown et al., 1975, p. 154). Once again if the regression assumptions are satisfied then these quantities should stay within defined limits.

Below we once again illustrate the case of two models, one showing stability and one

not showing stability. Note that as we plot this statistic from observation  $p+1$  to observation  $n$ , it must take on a value of unity at the limit (i.e. at observation  $n$ ).



### 3. Results

We now present values of the above statistics for influential observations and for structural breaks for the case of doctors' fees. We are concerned only with the pure time-series properties of doctors' fees, hence our regression model will only have time and higher order terms in time as explanatory variables. Ideally we would like to estimate a structural or even reduced form of inverse demand function whereby doctors' fees would depend upon such factors as underlying health, supply of GPs etc. Such data is simply not available and so we concentrate purely on the time series properties of doctors' fees.

There are a variety of models we could estimate to investigate the pure time-series properties of doctors' fees. Perhaps the simplest is where we simply let doctors' fees depend upon an  $n$ -th order polynomial in time. For comparison we include results for

a quadratic, cubic and quartic in time. For the case of leverage, standardised residuals and studentised residuals we present those observations with the five highest values. For the other statistics outlined above we list those observations in excess of the critical values suggested by Belsley, Kuh and Welsch (1980).

The results for influential observations do not lend any support to the idea that 1989 is in any way “different” in the sense that the relationship between doctors’ fees and time is unduly influenced by events in this year. In no case does an observation from 1989 exceed the critical value, nor are they ranked high in terms of leverage or the standardised or studentised residuals. What is of interest is to examine what observations, if any, consistently appear to be influential. In terms of residuals, it is clear that the first two quarters of 2002 and, to a lesser extent, of 1994 are outliers. As suggested above, the behaviour of doctors’ fees in early 2002 is probably due to rounding up following the introduction of the euro. It is less clear what caused the higher residuals in 1994.

In terms of leverage, the greatest influence is exerted by observations at the beginning and end of the sample period. In the case of the various measures combining residuals and leverage, the influence of large outliers appears to dominate that of observations with high leverage. Hence 2002 Q1 has the highest value of DFITS, Cook’s and Welsch’s Distance. For COVRATIO it is generally those observations with highest leverage which exert the most influence.

Turning now to the results for structural breaks, when we calculate the Chow statistic above for the quadratic, cubic and quartic in time for our data using 1989 Q1 as the date for the structural shift we obtain F values of 125.74, 117.24 and 100.01 respectively, clearly rejecting the null hypothesis that there is no structural shift. So, is this clear evidence that doctors’ fees did take a jump in 1989? Not really, since if

we calculate the same statistic for different dates, chosen somewhat randomly, then we also obtain high F values. For example, choosing 1986 Q1 we obtain F values of 129.19, 119.41 and 96.74 respectively, while choosing 1995 Q1 we obtain 97.63, 78.57 and 79.48. Thus while the Chow Test can tell whether the relationship has changed for two different periods with the cut-off date chosen arbitrarily, it does not identify when exactly the relationship begins to change.

In figures 1a to 4b we present the plots of the CUSUM and CUSUMSQ for the different regression models estimated for doctors' fees, while in table 3 we show for what quarter, if any, the CUSUM and CUSUMSQ plots move outside the 95% confidence intervals and for what quarter, if any, they move back inside the limits.

The results for CUSUM show no consistency in terms of when a regime change may have occurred. Those for CUSUMSQ do show consistency, with evidence of a change in regime sometime in 1988. This, however, pre-dates the change in reimbursement so unless GPs were demonstrating an unusual degree of foresight it seems unlikely that the change in reimbursement was the source of this regime change.

#### **4. Discussion and Conclusion**

This paper has extended the analysis of MNN's investigation into the presence of supplier induced demand in the Irish health system. An analysis of the time-series properties of doctors' fees gave no indication that there was any unusual upwards "blip" around about the time the reimbursement change was introduced in 1989. This finding is consistent with the conclusions of MNN who had used the reimbursement change as a natural experiment in their investigation into the presence of supplier induced demand in the Irish health system and concluded that no such inducement



existed. The analysis concludes that to the extent that any period could be identified where doctors fees did appear to behave unusually it was 2002 Q1, the period when the changeover to the euro occurred and when there was some anecdotal evidence of prices being rounded up.

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**Table 1: Residuals and Leverage Tables**

	<b>Quadratic</b>	<b>Cubic</b>	<b>Quartic</b>
<b>Residual</b>	1993q3 4.040937 1994q2 4.075958 1994q1 4.41813 2002q2 5.803434 2002q1 11.10708	1983q1 4.159307 1994q2 4.314041 1994q1 4.597921 2002q2 5.249311 2002q1 10.71379	1994q2 3.326477 1994q1 3.566862 2001q4 4.052376 2002q2 5.156991 2002q1 10.93967
<b>Leverage</b>	1983q3 .0849845 2003q2 .0937705 1983q2 .0937705 2003q3 .1033715 1983q1 .1033715	2003q1 .1224355 2003q2 .1469544 1983q2 .1469544 2003q3 .1763529 1983q1 .1763529	2003q1 .1472167 2003q2 .1956615 1983q2 .1956646 2003q3 .2615539 1983q1 .261558
<b>Standardised Residual</b>	1993q3 1.614895 1994q2 1.628505 1994q1 1.765409 2002q2 2.363393 2002q1 4.508962	1994q2 1.772296 1983q1 1.855927 1994q1 1.888412 2002q2 2.207103 2002q1 4.47928	1994q2 1.491997 1994q1 1.600324 2001q4 1.832766 2002q2 2.352024 2002q1 4.962735
<b>Studentised Residual</b>	1993q3 1.631584 1994q2 1.645804 1994q1 1.789546 2002q2 2.435124 2002q1 5.188176	1994q2 1.797132 1983q1 1.885711 1994q1 1.920263 2002q2 2.264002 2002q1 5.153057	1994q2 1.504019 1994q1 1.616797 2001q4 1.861503 2002q2 2.424454 2002q1 5.960912

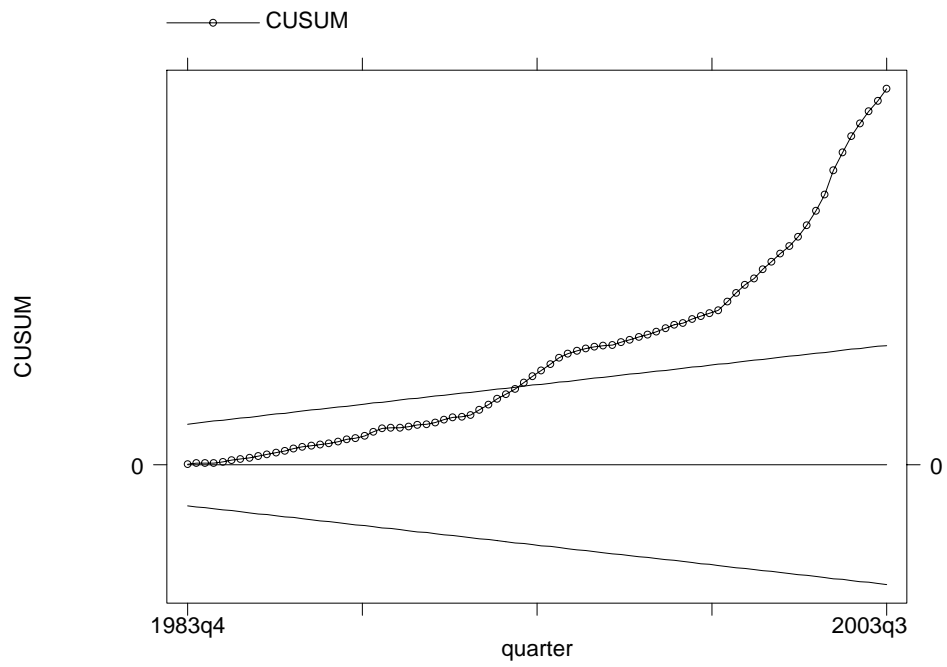
<b>Table 2: DFITS, Cook's Distance, Welsch's Distance and COVRATIO Tables</b>			
	<b>Quadratic</b>	<b>Cubic</b>	<b>Quartic</b>
<b>DFITS</b>	2002q3 .4173948 2002q2 .6319016 2002q1 1.277219	1983q2 .4850934 1983q1 .8725609 2002q2 .6323084 2002q1 1.322664	1983q1 .48272 2001q4 .4566158 2002q2 .6776755 2002q1 1.538692
<b>Cook's Distance</b>	2002q3 .0571261 2002q2 .1253739 2002q1 .4107081	2003q2 .0896757 2003q3 .0493738 1983q2 .0585576 1983q1 .1843755 2002q2 .0949926 2002q1 .3304649	2003q2 .3196336 2003q3 .4125764 2003q1 .061532 2002q2 .0864429 2002q1 .3282086
<b>Welsch's Distance</b>	2002q2 5.91163 2002q1 11.91102	1983q1 8.706269 2002q1 12.36548	2002q2 6.37183 2002q1 14.39016
<b>DFBETA (q)</b>	2002q1 -.6726409 2002q2 -.3538598 1994q1 .2204721 2002q3 -.2464218 1983q1 -.2877555	2002q1 .2896095 1998q3 .2200425 1983q1 -.6140192 2003q2 -.3263205 1983q2 -.3218166 2003q3 -.2590429	2003q2 .5760458 2003q3 .7550463 1983q1 -.3070806
<b>DFBETA (q<sup>2</sup>)</b>	2002q1 .7438254 2002q2 .3884256 2002q3 .2688075 1983q1 .2713457	2002q1 -.3240395 1998q3 -.2253262 1983q1 .5864317 2003q2 .3441555 1983q2 .3060353 2003q3 .2721687	2003q2 -.6012018 2003q3 -.7846808 1983q1 .2958201
<b>DFBETA (q<sup>3</sup>)</b>		2002q1 .3635265 2002q2 .2263039 1998q3 .2283469 1983q1 -.5613201 2003q2 -.3628275 1983q2 -.2918263 2003q3 -.2857441	2003q2 .6275222 2003q3 .8152993 1983q1 -.2853069
<b>DFBETA (q<sup>4</sup>)</b>			2003q2 -.6548761 2003q3 -.8466979 2003q1 -.2287365 1983q1 .2755144
<b>COVRATIO</b>	1983q4 1.124759 1983q2 1.132886 2003q1 1.134225 1983q3 1.134871 2003q3 1.155496	2002q1 .3474203 1983q2 1.150797 1983q4 1.166584 2002q4 1.171982 2003q1 1.176337 1983q3 1.186772 2003q3 1.218951	2002q1 .1706468 2002q2 .7960646 2003q2 .8541124 1984q1 1.16814 2002q4 1.186107 1983q4 1.201302 1983q3 1.248664 1983q2 1.315668 1983q1 1.384297

**Table 3: “Break-Out” Quarters for Doctors’ Fees**

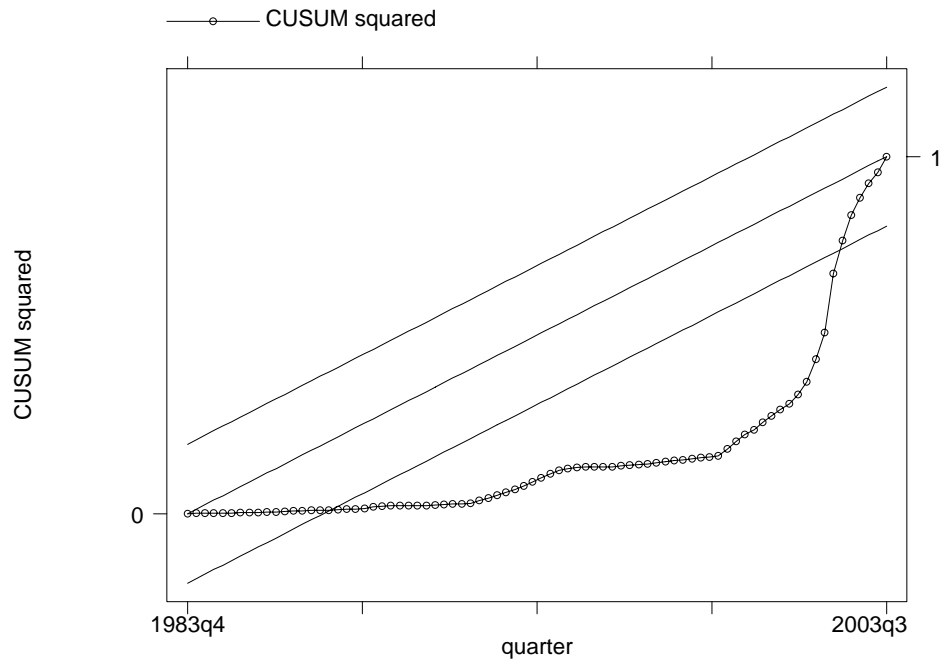
Break Out Quarters				
	Linear	Quadratic	Cubic	Quartic
CUSUM	1993 q2	1997 q4	2001 q4	-
CUSUMSQ	1988 q1	1988 q2	1988 q2	1988 q3

Break In Quarters				
	Linear	Quadratic	Cubic	Quartic
CUSUM	-	1999 q3	-	-
CUSUMSQ	2002 q2	2002 q1	2002 q1	2003 q1

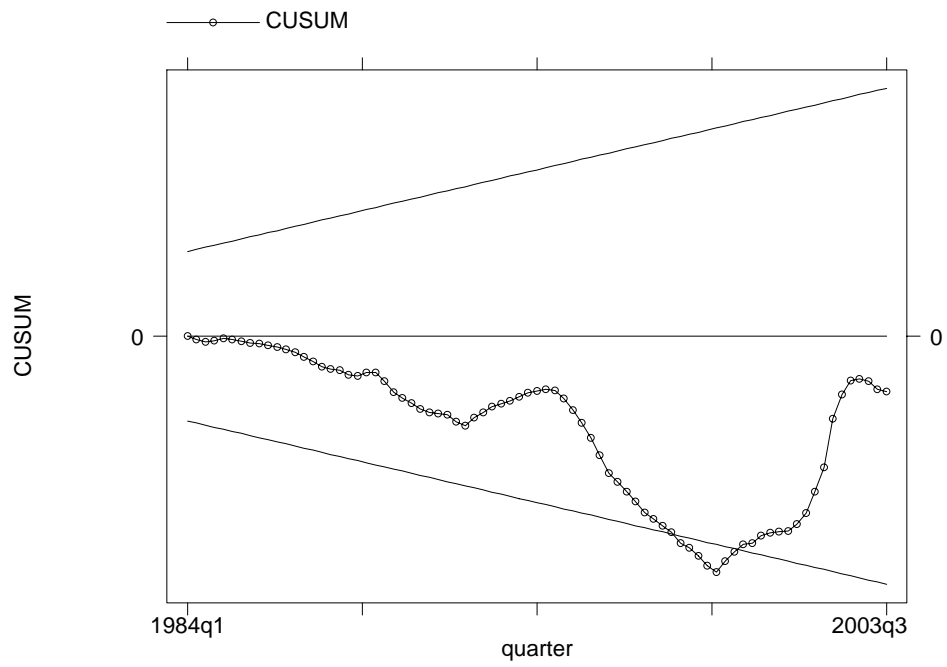
**Figure 1a: CUSUM plot for linear regression against time**



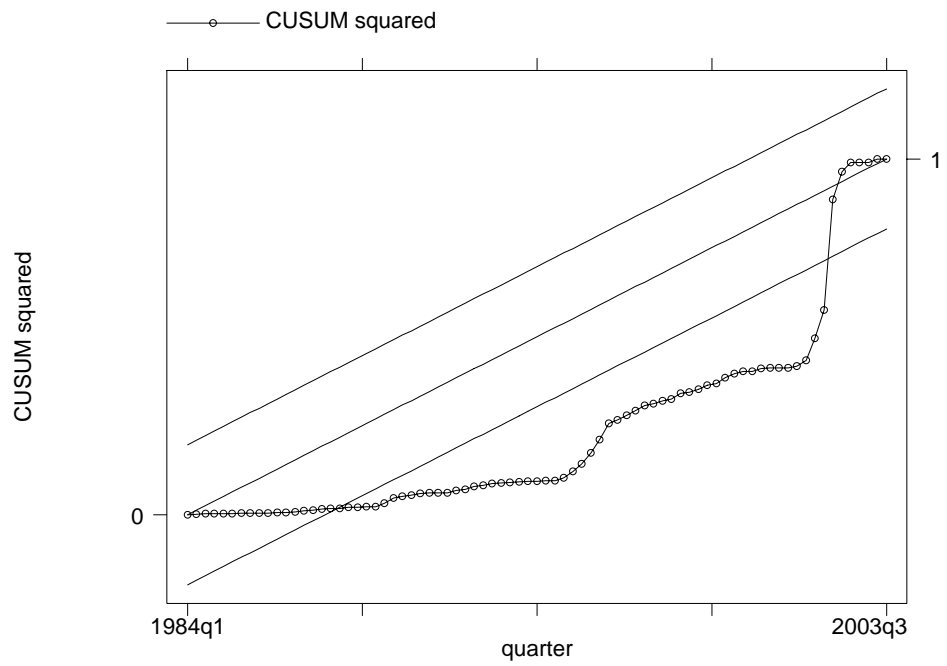
**Figure 1b: CUSUMSQ plot for linear regression against time**



**Figure 2a: CUSUM plot for quadratic regression against time**

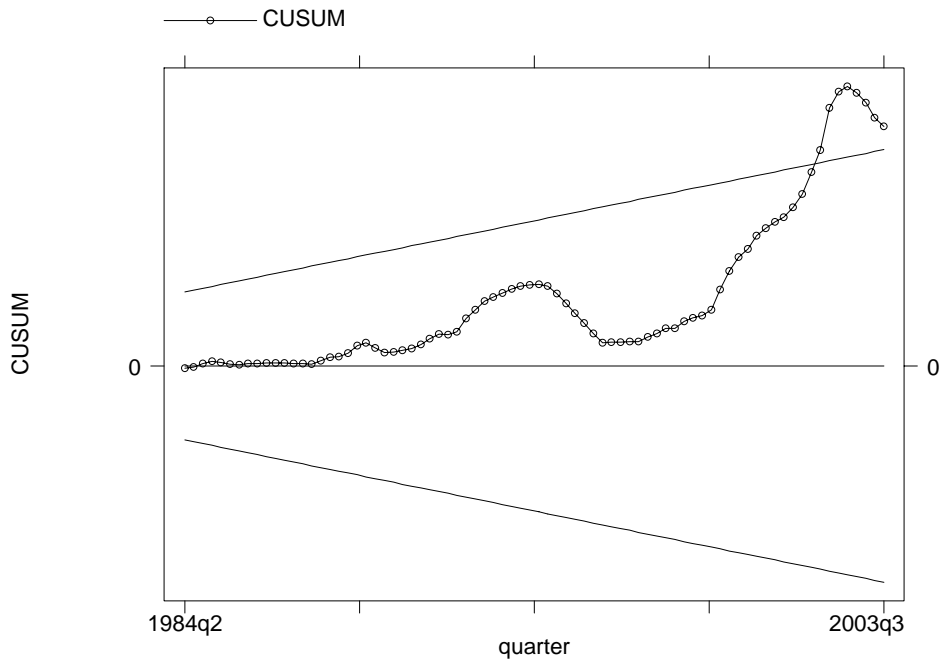


**Figure 2b: CUSUMSQ plot for quadratic regression against time**

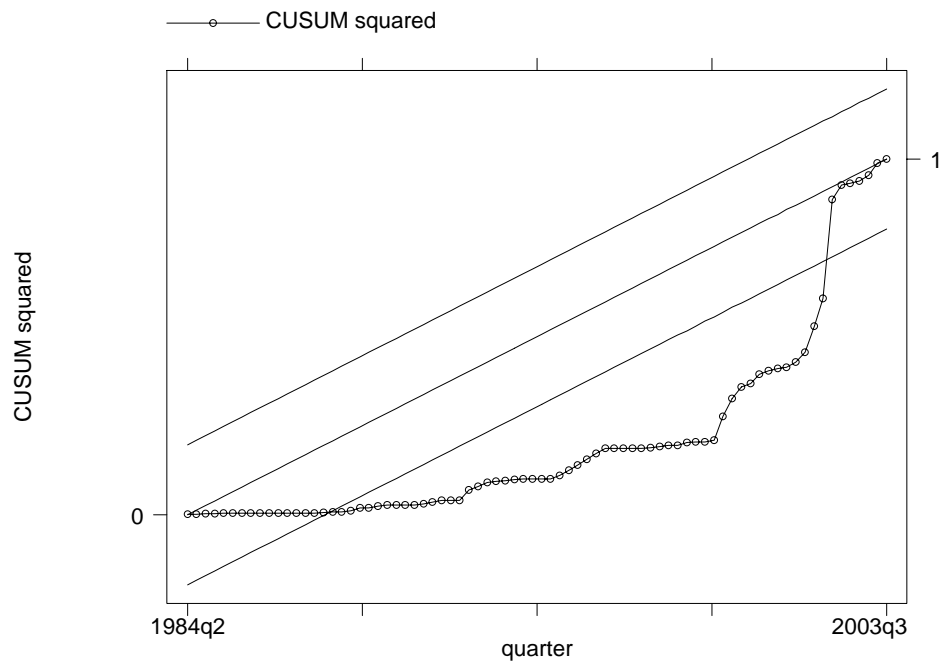




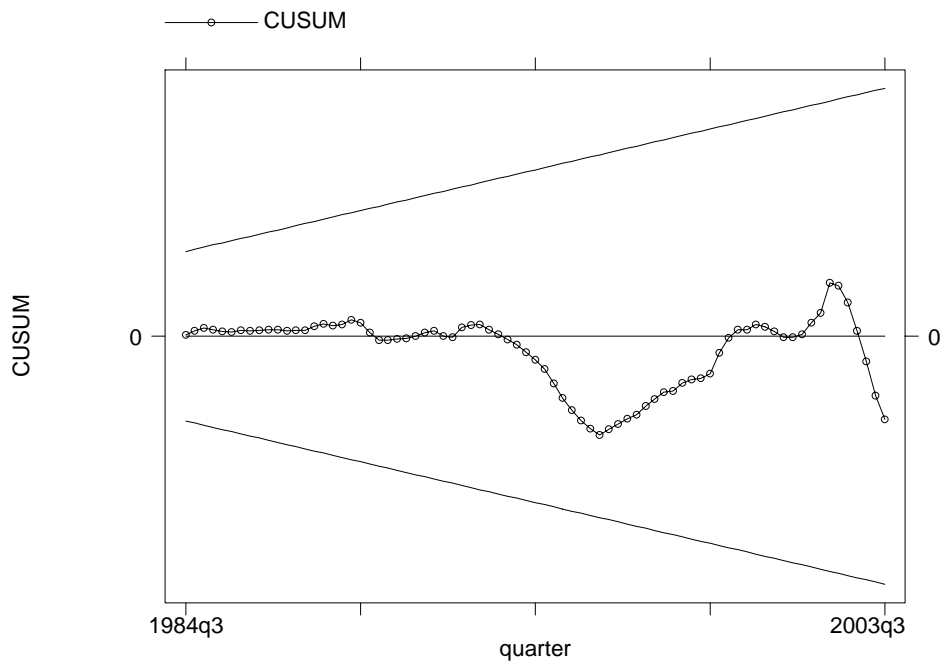
**Figure 3a: CUSUM plot for cubic regression against time**



**Figure 3b: CUSUMSQ plot for cubic regression against time**



**Figure 4a: CUSUM plot for quartic regression against time**



**Figure 4b: CUSUMSQ plot for quartic regression against time**

