Anticipation of monetary policy in UK financial markets

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Abstract

This paper examines the question of whether the ability of market interest rates to predict future policy rate changes in the United Kingdom has changed markedly over the period 1975-2003. Such improvements in predictability could arise from greater transparency in the monetary policy process, together with greater credibility of the Bank of England. Empirical tests, using a simple term structure model, show that predictability has indeed improved over the sample period as a whole, and most markedly after the introduction of inflation targeting in 1992. But closer inspection of the data reveals that predictability did not rise smoothly over time, nor is it possible to generalise this result across maturities. Furthermore, attempts to identify structural breakpoints in a formal way were on the whole unsuccessful. Nonetheless, the paper concludes that, over the longer sample period, the data show a clear improvement in the ability of market participants to predict policy rate changes by the Bank of England.

Summary

Monetary policy directly affects the shortest interest rates in the market. But if market participants are forward looking, then their expectations of future policy actions, and hence future short-term interest rates, will affect longer-term rates. This is a crucial aspect of the transmission of monetary policy. If monetary policy is stable and well understood, then market participants might be able to anticipate future policy decisions. Consequently, we would expect market interest rates to contain information about future policy rate changes.

This paper examines whether the ability of UK market interest rates to predict future policy rate changes has changed markedly over the period 1975-2003. It starts by reviewing the theoretical ideas supporting monetary policy predictability. Theory shows that this predictability could increase as a result of central banks' committment to gradualism in their rate-setting, or as a result of increased transparency (though this is by no means guaranteed). But increased predictability could also simply reflect reduced macroeconomic uncertainty unrelated to monetary policy. Theory is less clear, however, on the nature of the relationship between the monetary policy regime (eg money supply versus inflation targeting) and predictability.

Empirically, we can test the degree to which market rates anticipate future policy rate changes by examining the dynamic relationship between market and policy rate changes. In the United States, researchers have found evidence of predictability at the shortest end of the yield curve, although they also show that this predictability holds over very short horizons only. Recent work has revealed that this predictability varies over time. In particular, these studies show that since the mid-1990s, market rates have become better predictors of Federal Reserve policy changes, and that the predictability horizon has lengthened. While these studies admit that this shift cannot be attributed to a single factor, they cite the improved transparency of the Federal Reserve 's monetary policy as a key factor in improving market participants' ability to anticipate future policy rate changes.

In this paper, we conduct a similar analysis for UK rates in the period 1975-2003. During this period, the monetary framework changed from (albeit not pure) monetary targeting (1975-85) to (various forms of) exchange rate targeting (1985-92) and since, 1992, inflation rate targeting. In addition, monetary policy has become more transparent, with the introduction of scheduled

meetings to discuss policy rate changes (October 1992), the publication of the *Inflation Report* (February 1993), the decision to publish the minutes of the monthly interest rate meetings (April 1994), and the creation of the Monetary Policy Committee (May 1997).

We start by estimating a simple term structure model and introduce exogenous breakpoints corresponding to the key policy changes. The results of this analysis indicate that predictability has improved most notably after the introduction of inflation targeting in October 1992. But closer inspection of the data reveals that predictability did not rise smoothly over time, nor is it possible to generalise this result across maturities. For example, at the longest horizon, it rose briefly after the introduction of the Medium Term Financial Strategy in March 1980 and plummeted after the suspension of ERM membership in September 1992. Rolling regressions show that in the 1980s and early 1990s predictability fluctuated between 0% and 60%, with frequent highs and lows in predictability seemingly unrelated to any policy changes.

Finally, we formally test for the presence of structural breaks in the term structure model without using any prior information on the location of potential breaks. This is done by employing the recently developed method of Bai and Perron. Unfortunately, this exercise was on the whole unsuccessful, as the tests did generally not identify the earlier-used exogenous breakpoints. We attribute this result to either the unknown power properties of the Bai and Perron method, misspecification of the term structure model, or gradual (as opposed to discrete) shifts in the term structure model possibly due to learning.

Despite this mixed evidence, we conclude that, over the longer sample period, the data show a clear improvement in the ability of market participants to predict policy rate changes by the Bank of England.

1 Introduction

Monetary policy directly affects the shortest interest rates in the market. But if market participants are forward looking, then their expectations of future policy actions, and hence future short-term interest rates, will affect longer-term rates. This is a crucial aspect of the transmission of monetary policy. If monetary policy is stable and well understood, then market participants might be able to anticipate future policy decisions. Consequently, we would expect market interest rates to contain information about future policy rate changes.

Empirically, we can test the degree to which market rates anticipate future policy rate changes by examining the dynamic relationship between market and policy rate changes. In the United States, researchers have found evidence of predictability at the shortest end of the yield curve, although they also show that this predictability holds over very short horizons only. Recent work by Lange, Sack and Whitesell (2003) and Swanson (2003) has revealed that predictability varies over time. Both studies show that since the mid-1990s, market rates have become better predictors of the Federal Reserve's monetary policy changes, and that the predictability horizon has lengthened. In this paper, we conduct a similar analysis for UK rates in the period 1975-2003. Given that our data set covers a long period, during which monetary policy underwent significant changes, we would not expect the relationship between market and policy rates to stay the same over time. For this reason, we will be particularly interested in the outcome of structural breakpoint tests. We also acknowledge that increased predictability may simply reflect reduced macroeconomic uncertainty unrelated to monetary policy. Although this is not the main focus of the paper, we briefly discuss how it might affect the interpretation of our results.

Predictability of policy rate changes is not inconsistent with optimal monetary policy. In the next section, we review the theory and describe the factors that can be expected to contribute to predictability. Section 3 outlines the empirical model employed in the paper and Section 4 surveys the empirical literature on monetary policy predictability. The data set is presented in Section 5, and empirical results are available in Section 6. Section 7 concludes.

2 Monetary policy and predictability

In this section, we review the theoretical ideas underpinning predictability of monetary policy. These include central bank preferences for low interest rate volatility, macroeconomic uncertainty and transparency of the policy process. We also outline how changes of the United Kingdom's monetary policy over the past two decades can be descibed within this conceptual framework.

2.1 A theoretical framework

In most developed countries, central banks conduct their monetary policy either by targeting a short-term market interest rate or by setting an official interest rate for their open market operations. These policy rates anchor the entire term structure of interest rates. At very short maturities, monetary policy directly affects market interest rates via normal arbitrage mechanisms. At longer maturities, monetary policy has a less direct effect since these market interest rates depend on market participants' expectations of future policy rate changes. The relationship between market interest rates and policy rates implies that one can study market rates' ability to predict future policy rate changes. One can also assess whether this predictability changes over time.

One view of monetary policy is that if shocks arrive in a random fashion, the optimal policy response is equally unanticipated, and policy rates will be unpredictable. But this view is at odds with the practice of many central banks to implement monetary policy via a succession of small rate changes in the same direction, and to reverse the direction of interest rate changes only infrequently (eg Rudebusch (2002)). Hence, an alternative view is that central banks prefer to adjust policy rates slowly towards their desired target. The early literature attributes this so-called monetary policy inertia to either central banks' preference for interest rate smoothing, or to their slow response to new information. In other words, central banks were believed to have an interest rate smoothing objective, in addition to their inflation and output stabilisation goals. A large empirical literature also exists that incoporates interest rate smoothing in the estimation of policy rules (see Clarida, Gali and Gertler (1999)). In general, these studies find rules that allow for a degree of interest rate smoothing to provide a better explanation of the data.

But recent research in the United States and the United Kingdom has demonstrated that such interest rate smoothing (also refered to as gradualism) might constitute an optimal response to shocks hitting the economy if economic agents are forward looking. Woodford (1999) argues that if a central bank has established a reputation for either keeping rates at the same level for an extended period of time, or for implementing successive, small changes after an initial move, it effectively has committed itself to a path of future short rates. Market participants will incorporate these beliefs into their expectations of future short-term rates, and longer-term rates will reflect the central bank's expected future policy rate changes. In other words, Woodford (1999) shows that it is optimal for the central bank to commit to inertia. This has two implications. First, the central bank will be able to achieve its long-term objectives (of price and/or output stability) without excessive short-term interest rate volatility, and second, market interest rates will contain information about future policy rates. Goodfriend (1998) refers to this as 'policy in the pipeline', and argues that if the market correctly anticipates future policy decisions, then future policy changes are reflected in market interest rates before being implemented by the central bank. This is because market interest rates will not only reflect the first policy rate change, but also the sequence of expected future rate changes in the same direction.

Sack (2000) and Sack and Wieland (2000) show that gradualism might also constitute an optimal response to economic shocks when central banks are uncertain about either economic data or economic relationships. Since this uncertainty also affects the economic models central banks employ when considering their policy decisions, the research, initiated by Brainard (1997), indicates that it might be optimal for central bankers to adjust policy rates in a smoother way than in the certainty case. Sack and Wieland (2000) argue that forward-looking expectations, together with data and model uncertainty can explain much of the observed gradualism of US monetary policy in the 1980s and 1990s. A similar analysis is conducted for the United Kingdom by Martin and Salmon (1999). Their results confirm the presence of gradualism in UK policy, but cannot explain the occurrence of rate reversals. To the extent, however, that policymakers have become increasingly aware of these uncertainty issues, monetary policy may have become more gradual and hence more predicable over time.

But increased predictability could also be the result of changes in the dynamic structure of the economy unrelated to monetary policy. If shocks hitting the economy become more persistent (or serially correlated) over time, then the central bank's response to these shocks would appear increasingly persistent, even in the absence of a preference for interest rate smoothing. This in turn would increase the predictability of policy rate changes, in much the same way as our earlier discussion of gradualism outlined. Sack (2000) uses a VAR analysis to examine the response of the Federal Reserve to shocks in unemployment, production and inflation. His simulations show that the persistence in the innovations to these economic variables leads to a more gradual response than an optimal policy rule would indicate. Nonetheless, his results also indicate that the observed degree of gradualism in monetary policy is too high to be attributed to the Federal Reserve's response to persistent economic shocks.[1] A similar result is found for the United Kingdom by Goodhart (1999). A different view is taken by Rudebusch (2002) who argues that the amount of interest rate smoothing in the setting of US monetary policy is negligible. In particular, he shows that the amount of policy inertia typically found in US data is inconsistent with the limited amount of information in financial markets data regarding future interest rate movements.

Greater transparency of the central bank's policy making is considered another factor contributing to greater predictability. Central bank transparency is defined as the absence of asymmetric information between the policymaker and economic agents, see Geraats (2003). It is believed to reduce uncertainty and consequently to reduce forecast errors. In this view, greater transparency allows market participants to anticipate future policy rate decisions with a greater degree of accuracy, thereby leading to improved predictability. This relationship between transparency and predictability contributes to the informativeness of market interest rates and facilitates the implementation of monetary policy, along the lines suggested by Woodford and Goodfriend.

It is generally accepted, however, that neither full transparency nor full predictability can be attained in a world of uncertainty. While central banks prefer to avoid surprises (King (1997)), Vickers (1998) acknowledges that monetary policy 'cannot be absolutely transparent, nor totally boring' as monetary policy is a highly complex decision making process, particularly when decisions are made collectively. It should also be pointed out that greater transparency does not always lead to a reduction of uncertainty. Geraat (2003)'s survey convincingly shows that the uncertainty reduction effect depends very much on the specific policy context. She provides several examples where some opacity of the central bank's preferences is beneficial. For example, when the public is uncertain about the central bank's relative preferences for output and inflation stabilisation, increased transparency might in some cases generate higher private sector inflation expectations and increased inflation variability, which could in turn affect their expectations of

(1) Within the framework employed in the present paper, it is not possible to disentangle these factors, and neither does Lange, Sack and Whitesell (2003).

future policy rates. Furthermore, increased tansparency about economic variables or forecasts leads in some, but not all circumstances, to reduced variablility of inflation and output.

Increased transparency can be achieved through a range of measures aimed at providing the public with more information about the monetary policy process. These include measures that promote goal transparency (about the central bank's objectives), economic transparency (the economic information used to make policy decisions) and procedural transparency (how the decision is reached). The adoption of explicit inflation targets as a way to enhance goal transparency deserves a special mention. Since the adoption of an inflation target is often accompanied by a more systematic communication of its policy decisions (eg via the publication of an inflation forecast), it signals both the central bank's commitment to an implicit policy rule (see Svensson (2003)) and to increased transparency.

This raises the more general question as to when, in the absence of steps to release more information, a change from one monetary policy regime to another leads to increased predictability. In other words, are some monetary policy regimes associated with greater predictability?

Woodford (2003) argues that the commitment of central banks since the 1980s to a more systematic monetary policy relying on policy rules has led to a greater public understanding of policy. Via their effect on private sector expectations of future economic conditions, policy rules facilitate the central bank's stability objectives (as explained in the discussion of gradualism) and contribute to greater monetary policy predictability. But Woodford (2003) also conveys the widely held view that the mechanical rules of the 1970s and 1980s did not always achieve this. In spite of their apparent transparency (eg a simple money supply target), they did not always give the monetary authority the flexibility needed to respond to economic shocks. As a result, they often generated a substantial amount of uncertainty (eg widely fluctuating interest rates). In that sense, mechnical rules frequently harmed interest rate predictability, rather than promoted it. In contrast, forward-looking rules, increasingly popular in the 1990s, allow for a more flexible and systematic response to economic shocks, and could therefore lead to greater interest rate predictability. Examples include Taylor rules that respond to inflation and the output gap, inflation rules that target expected inflation at a specified horizon, or more complex targeting rules where the central bank's response to the inflation target depends on the output gap as well (see Svensson (2003)).

Transparency choices further complicate our assessment of the relative predictability associated with different policy regimes. This is usefully illustrated in Faust and Svensson (200), who sketch a general framework where the central bank chooses its level of transparency, together with its degree of commitment. They show that a central bank that is committed to a policy rule and has a low inflation bias, will tend to choose a low level of transparency. But if the central bank cannot commit, then their model can generate an equilibrium with both minimal and full transparency. Consequently, it is not clear which monetary policy will be most predictable: that of the low-transparency, committed central bank, or that of the high-transparency, discretionary central bank.

In the next section, we examine how the United Kingdom's recent monetary experience can be described within the theoretical framework outlined above.

2.2 The UK experience

In the United Kingdom, the monetary policy framework has undergone important changes in the past three decades.[(2)] Between 1976 and 1985, the Bank of England conducted policy in a monetary targeting framework. In July 1976, a target for broad money supply (£M3) was introduced as a response to the 1976 exchange rate crisis. But UK authorities continued to rely on a combination of direct controls (prices, wages, credit) and fiscal policy in order to combat inflation. Direct credit controls were abolished shortly after the abolition of exchange controls in autumn 1979. In spite of frequently missing the £M3 monetary target, the UK government re-affirmed its commitment to a monetary target in the Medium Term Financial Strategy (MTFS) in March 1980. As part of this strategy, a monetary target range was set over a medium-term horizon (four years), and all other macroeconomic policies were subordinated to the achievement of this target. Goodhart (1989b) writes that 'the terms in which the Chancellor described his adherence to the £M3 target implied an unprecedented degree of commitment'. Nonetheless, monetary policy continued to be dominated by other policy considerations (eg concerns with a rising exchange rate after 1979 and with domestic credit expansion in 1982-85) and official interest rates were raised sharply several times, to reach a peak of 17% in November 1979. The introduction of additional money supply targets in March 1982 further undermined the public's confidence in the monetary authorities' commitment to monetary targeting. The £M3 money

(2) For more detail, see Fforde (1983), Coleby (1983), Goodhart (1989a), Goodhart (1989b), Minford (1993) and Nelson (2000).

target was officially abandoned in October 1985.

After the formal suspension of the £M3 target, and in light of the instability in foreign exchange rate markets experienced during the early 1980s, monetary policy in the United Kingdom, as elsewhere, was increasingly conducted with an eye on stabilising exchange rate movements. Between 1987 and 1988, the pound remained within a fairly narrow range against the DM. Thereafter, the United Kingdom continued to follow German monetary policy, until formally joining the Exchange Rate Mechanism (ERM) in September 1990. Nonetheless, a monetary target for narrow money (M0) remained in place until 1992. Since leaving the ERM in September 1992, UK monetary policy has been conducted in an inflation targetting framework.

King (2002) argues that the introduction of an explicit target for inflation in 1992 led to a stable and predictable policy environment, with inflation expectations firmly anchored around the target. In the light of the preceeding discussion on factors affecting predictability, we might indeed expect to see a rise in predictability after September 1992. But this could stem from either the change in policy (ie from a simple exchange rate rule to a forward-looking inflation target), from a firm commitment to the new policy, or from both. The theory outlined in Section 2.1 also suggests that it might be difficult to predict the change in predictability associated with the move from a money supply to an exchange rate target, both examples of mechanical rules, as not only the policy instrument, but also the nature of economic shocks may have changed.

After 1992, a number of institutional reforms further improved the transparency of the UK policy process. As indicated in the preceeding section, it is possible that these contributed to further increases in predictatility, but this is by no means guaranteed. Transparency-improving reforms included the introduction of scheduled meetings to discuss policy rate changes (October 1992), the publication of the *Inflation Report* (February 1993), the decision to publish the minutes of the monthly interest rate meetings (April 1994) and the creation of the Monetary Policy Committee in 1997. Also since 1997, the minutes have included the MPC’s votes, together with a range of views on the policy decision. In October 1998, the minutes’ publication delay was reduced from six to two weeks.

We conclude the present section by examining UK official rate changes. Chart 1 presents official interest rates between 1975 and 2003 and shows that rate volatility was particularly high between

1975 and 1985. However, subsequent rate volatility did not decline substantially until late 1992.[3] A histogram of rate changes (Table A) confirms that the early period saw many more large policy rate changes than the later years. For example, out of 88 rate changes between January 1975 and October 1985, 32 were of a magnitude of 100 basis points or larger. This number fell to 12 between November 1985 and September 1992. After this date, there were only three policy changes of 100 basis points, the last one in January 1993. The table further shows that the range of policy rate moves changed after 1985, with rate changes being either 25 or 50 basis points (except for the earlier-mentioned 100 basis points following the ERM crisis). Prior to that date, UK authorities used both finer changes (12.5 and 25 basis points), as well as larger ones (150, 200 and 300 basis points). Finally, Table A indicates that the frequency of rate reversals declined over time. Specifically, they fell from 24 (out of 88 changes) in the period 1975-85 to 12 (out of 41 changes) in the period 1985-92. After September 1992, a total of 37 rate changes were implemented, of which only six constituted a change in direction. This is consistent with the increased gradualism in UK monetary policy discussed earlier. In fact, the period after September 1992 contains the longest period of unchanged official UK interest rates (November 2001 to February 2003) since the period from February 1964 to June 1965.

To conclude, data on official rates suggest that the pattern of interest rate setting by the UK authorities has changed over time. In the next section, we outline an empirical model that allows us to quantify whether this has led to increased predictability in market interest rates.

3 Method

To explore whether the ability of financial markets to predict future interest rates has changed over time, we first need to define how to extract expectations of future interest rates from market interest rates, and second decide how to evaluate the performance of these expectations. That is the purpose of Sections 3.1 and 3.2, respectively.

3.1 Extracting expectations from financial markets

Various financial markets embed market participants' expectations of future interest rates. We choose to focus on the sterling interbank deposit market, because related data - the London

(3) This histogram does not include the decision to raise the policy rate to 15% on 16 September, 1992, as it was rescinded later in the day.

Interbank Offer Rate (Libor) - span a long period. Libor rates are collected from a panel of major international banks and represents the average rate at which a subset of the panel expects to be offered funds from another bank in the market. It therefore contains a small element of credit risk. To extract market expectations, we need a term structure model. The most commonly used is based on the Expectations Hypothesis (EH).[(4)] In its simplest form, the EH states that the interest rate of a long-dated bond (denoted by $y_{n,t}$) equals the average of current and future expected short-term rates (short-term rate is denoted by $y_{m,t}$) over the holding period of the long bond. To see how this model is derived, we construct a simple example that compares two investment strategies from day t to day t+1 in the bond market. The first strategy consists of buying a one-day bond. This is a safe strategy, with return given by $y_{1,t}$.[(5)] In the second strategy, we buy an n-day bond today and sell it at the beginning of tomorrow. In contrast to the first strategy, this is an uncertain or risky strategy because we do not know its future cash flow (the price of an (n-1)-day bond tomorrow morning). The expected return on this investment is given by $E_t\left[r_{n,t+1}\right]$. In a risk-neutral setup, the two investment strategies of our example yield the same expected returns. But, standard asset pricing theory augments the return on the risky strategy above, the one-day bond return, with a risk premium $\eta_{n,t}$, eg Campbell and Shiller (1991).

$$E_t\left[r_{n,t+1}\right] = y_{1,t} + \eta_{n,t} \qquad \textbf{(1)}$$

This risk or term premium compensates the investor for the risk associated with the riskier strategy (which as said earlier has an unknown future pay-off). Equation **(1)** produces the log Expectations Hypothesis, if one restricts the risk premium $\eta_{n,t}$ to be time-invariant:[(6)]

$$E_t\left[r_{n,t+1}\right] = y_{1,t} + \eta_n \qquad \textbf{(2)}$$

It can be shown that equation **(2)** can be rewritten as[(7)]

$$s_{(n,m),t} = E_t\left[c_{(n,m),t}\right] + \gamma_{n,m}, \qquad \frac{n}{m} \text{ is an integer value} \qquad \textbf{(3)}$$

where

$$s_{(n,m),t} = y_{n,t} - y_{m,t} \qquad \textbf{(4)}$$

is the spread between the n-day yield and the m-day yield, and

$$c_{(n,m),t} = \sum_{i=1}^{\frac{n}{m}-1}\left(1 - \frac{i}{\frac{n}{m}}\right)\left(y_{m,t+im} - y_{m,t+(i-1)m}\right) \qquad \textbf{(5)}$$

(4) Although no longer at the frontier of term structure modelling, the expectations hypothesis remains one of the most popular models for thinking about interest rate expectations by both policymakers (eg Brooke, Cooper and Scholtes00) and academics (eg Cochrane (2001)).
(5) We define the holding period return on an n-period bond purchased at time t and sold at time $t+1$ as $r_{n,t+1}$. We use log returns, or in other words, we adopt continuous compounding.
(6) Eg Campbell and Shiller (1991).
(7) Derivations are available upon request.

measures future changes in the short rate $y_{m,t}$.

Equation **(3)** states that the spread between the *n*-period yield ($y_{n,t}$) and the *m*-period yield ($y_{m,t}$) equals a weighted average of expected future changes in the short-term rate ($y_{m,t}$) plus a constant ($\gamma_{n,m}$). It is easy to show that $\gamma_{n,m}$ is a linear combination of various risk premia if the log Expectations Hypothesis holds. (8) The intuition of this equation is that if the yield on the long bond, $y_{n,t}$ is higher than the yield on the short period bond $y_{m,t}$, short rates are expected to rise so that the average short rate over the life of the long bond equals the initial long-bond yield. Since the EH applies to any combination of long and short rates, we can take the policy rate as our short rate ($y_{m,t}$). (9) Equation **(3)** can then be used to examine whether the spread of a given market rate over the official rate ($c_{(n,m),t}$) has predictive power for future official rates ($y_{m,t+i}$).

In the context of the United Kingdom, the official rate is approximately a two-week interest rate, so $m = 14$. To ease notation, we therefore rewrite equation **(3)**, dropping subscripts *m*

$$s_{n,t} = E_t\left[c_{n,t}\right] + \gamma_n, \qquad \frac{n}{14} \text{ is an integer value} \tag{6}$$

where

$$s_{n,t} = y_{n,t} - y_{14,t} \tag{7}$$

$$c_{n,t} = \sum_{i=1}^{\frac{n}{14}-1}\left(1 - \frac{i}{\frac{n}{14}}\right)\left(y_{14,t+i14} - y_{14,t+(i-1)14}\right) \tag{8}$$

$$\gamma_n = \gamma_{n,14}$$

Empirical work often rejects the log Expectations Hypothesis. There are various econometric and economic explanations of this finding which will not be covered in detail here, eg Bekaert, Hodrick and Marshall (1997), Campbell and Shiller (1991), and Kozicki and Tinsley (2001). For the purpose of this paper, the implication is that market expectations can *not* be extracted by re-arranging equation **(6)** to $E_t\left[c_{n,t}\right] = s_{n,t} - \gamma_n$, because this formulation of market expectations is mis-specified. But how then are market expectations formed ?

(8) Eg Chapter 10 in Campbell, Lo and MacKinlay (1997).
(9) By mixing Libor rates (unsecured lending) and policy rates (secured lending), we introduce an additional factor of credit risk into the risk premium, $\gamma_{n,m}$, in equation **(3)**. However, the effect of this distortion is likely to be minimal, except maybe in times of financial market turmoil (eg LTCM).

According to Campbell and Shiller (1991) the risk-premium γ_n in **(6)** is misspecified in the sense that it is not correlated with expected increases in the short rates. Similarly, Thornton (2002) claims that the risk-premium γ_n in **(6)** is misspecified because it does not depend linearly on the long rate $y_{n,t}$. The essence of these explanations is that rejection of the log Expectations Hypothesis is due to misspecification of the risk-premium because it is not specified as a linear function of the yield spread $s_{n,t}$, (Campbell and Shiller (1991)) or the long rate $y_{n,t}$, (Thornton (2002)).

These conjectures are consistent with a growing literature on yield curve modelling stressing the importance of time-varying risk premia. In what follows, we adopt Campbell and Shiller (1991)'s suggestion and modify equation **(6)** by redefining the constant term γ_n as an affine function of the slope of the yield curve

$$s_{n,t} = E_t\left[c_{n,t}\right] + \gamma_{n,t}, \qquad \frac{n}{14} \text{ is an integer value} \tag{9}$$

$$\gamma_{n,t} = (\alpha_n + \delta_n s_{n,t}), \qquad \delta_n > 0 \tag{10}$$

Rewriting **(9)** to get an expression for expected future changes in the short rate

$$E_t\left[c_{n,t}\right] = (1 - \delta_n)s_{n,t} - \alpha_n \tag{11}$$

The interpretation of equation **(11)** is that market expectations of future changes in the short rate can be expressed as an affine function of the yield spread. Campbell and Shiller (1991) refer to this model as an *overreaction model of the yield spread*. The log Expectations Hypothesis is obtained as a special case where the population value of β is unity and therefore δ_n is zero because the term premium must be time-invariant. Empirical estimates of equation **(11)** are obtained by regressing actual changes in the short rate $c_{n,t}$ on the spread $s_{n,t}$ and a constant:

$$c_{n,t} = \beta_n s_{n,t} - \alpha_n + u_{n,t}, \qquad \frac{n}{14} \text{is an integer value} \tag{12}$$

$$\beta_n = (1 - \delta_n) \tag{13}$$

So according to the model, estimates of market expectations are given by fitted values, $\widehat{c}_{n,t}$, from the linear regression model in **(12)**.

The error term $u_{n,t}$ contains an expectation error, which will be uncorrelated with the yield spread $s_{n,t}$ under the assumption of rational expectations. Furthermore, as can be seen from equation **(12)**, if the time span between adjacent data points is higher than n, the maturity of the long bond, then the regression will involve overlapping errors, and $u_{n,t}$ will be serially correlated (see Campbell and Shiller (1991) and Hodrick (1992)).

3.2 Evaluation of market expectations

The former section explained how to extract estimates of market expectations. In this section, we explore how to evaluate the performance of these estimates of expectations.

A common approach in forecast evaluation is to use a loss function $L(\widehat{c}_{n,t}, c_{n,t})$, which must obviously be a function of the expected value $\widehat{c}_{n,t}$ and the outcome $c_{n,t}$. By far the most common loss function adopted in statistics is a quadratic loss function

$$L(\widehat{c}_{n,t}, c_{n,t}) = (\widehat{c}_{n,t} - c_{n,t})^2$$

An estimator of the expected loss from a given set of forecasts $\widehat{c}_{n,t}$ is then given by the mean squared error criterion

$$MSE = \frac{\sum(\widehat{c}_{n,t} - c_{n,t})^2}{T}$$

In some cases, this quantity is expressed in term of the root-mean-square-error

$$RMSE = \sqrt{\frac{\sum(\widehat{c}_{n,t} - c_{n,t})^2}{T}}$$

Note that $\widehat{c}_{n,t} - c_{n,t} = \widehat{u}_{n,t}$, so the estimator of σ_{u_n}, the standard error of $u_{n,t}$,

$$\widehat{\sigma}_{u_n} = \sqrt{\frac{\sum_{t=1}^{T} \widehat{u}_{n,t}^2}{T}}$$

is identical to the RMSE criterion. Hence, we adopt $\widehat{\sigma}_{u_n}$ as a goodness-of-fit measure for the market expectations $\widehat{c}_{n,t}$. A low $\widehat{\sigma}_{u_n}$ is associated with a low average loss.

An alternative performance measure is given by the coefficient of determination R^2 from the regression in **(12)**. It describes how large a fraction of the variation in $c_{n,t}$ is explained by $s_{n,t}$. Obviously, a high R^2 indicates that the market is good at predicting future changes in the short rate $c_{n,t}$.

One could argue that the quadratic loss function used above does not provide a realistic representation of market participants' loss function. Alternatively, we adopt the linlin loss function

$$L^*(\widehat{c}_{n,t}, c_{n,t}; a, b) = \begin{cases} a \left|\widehat{c}_{n,t} - c_{n,t}\right| & \text{if} \quad \left(\widehat{c}_{n,t} - c_{n,t}\right) > 0 \\ b \left|\widehat{c}_{n,t} - c_{n,t}\right| & \text{if} \quad \left(\widehat{c}_{n,t} - c_{n,t}\right) \leq 0 \end{cases} \qquad \textbf{(14)}$$

used by Granger (1969). One motivation for this loss function is that it is asymmetric in losses, in the sense that positive and negative forecast errors of the same magnitude may not give rise to equal losses.[10] An estimator of the expected loss from a given set of forecasts $\widehat{c}_{n,t}$ is then given by the mean linlin loss

$$MLL_{(a,b)} = \frac{\sum L^*(\widehat{c}_{n,t}, c_{n,t}; a, b)}{T}$$

with parameters a and b. It is easy to show that the MLL criterion is linear in (a, b), so without loss of generality we normalize $a = 1$, and the criterion reduces to

$$MLL_b = \frac{\sum L^*(\widehat{c}_{n,t}, c_{n,t}; 1, b)}{T}$$

A low MLL_b is associated with a low loss and thereby a high degree of predictability.[11]

4 Existing empirical evidence

Previous work on the predictability of short-term interest rates has tended to focus on the United States. The earlier literature (eg Campbell and Shiller (1991) and Rudebusch (1995)) concluded that only the short end of the Treasury yield curve contained information for future policy rate decisions. Moreover, the predictability of short rates was found to improve with the length of the forecast horizon. In contrast, at longer maturities, such predictability was found to be largely absent.

More recent work has documented the time-varying nature of this short-term predictability. For example, Lange, Sack and Whitesell (2003) find that throughout the 1980s, market interest rates had predictive power for policy rate changes only one month ahead. But, from the late 1980s onwards, predictability improved significantly. In particular, from the mid-1990s onwards, market rates were found to forecast up to 70% of policy changes several months ahead. While the authors admit that this shift cannot be attributed to a single factor, they cite the improved transparency of the Federal Reserve's monetary policy[12] as a key factor in improving market participants' ability

(10) At least if $a \neq b$.
(11) One could argue that in the presence of a linlin loss function, the conditional mean, which is going to be used as the predictor of this paper (embodied in OLS regressions) is inadequate, as shown by Christoffersen and Diebold (1997). Instead the quantile regression approach would be suitable because the underlying loss function is linlin. However, we abstract from this interesting extension of the paper due to limitations of space.
(12) Eg the issue of a statement that includes the federal funds target after February 1994.

to anticipate future policy rate changes. Using a very similar method, Swanson (2003) finds that predictability has deteriorated since January 2001. The author attributes this to increased variability in the Federal Reserve's policy rate, January 2001 being the start of its most recent easing cycle. However, he also shows that the gains in forecast accuracy prior to that date were not the result of reduced policy rate variability, lower macroeconomic uncertainty or improved private sector macroeconomic forecasting ability. Instead, he attributes this improvement entirely to the greater transparency of the Federal Reserve, in particular the 1994 decision to announce all policy rate changes.

Lange, Sack and Whitesell(2003) also test the predictive ability of futures contracts, using the term structure method described in the previous section. In particular, they examine federal funds futures, which offer a payout based on the average federal funds rate over a particular month. In addition, these contracts are used to construct a measure of the unexpected component of Fed policy decisions. This 'policy surprise' was first introduced by Kuttner (2001) and Poole, Rasche and Thornton (2002). The analysis by Lange, Sack and Whitesell (2003) reveals that the predictive ability of futures contracts has increased over time, with the federal funds contract explaining around 80% of the change in actual policy rate changes from the mid-1990s onwards. This increase in predictive ability is shown to coincide with a decline in the unanticipated component of monetary policy, as measured by the policy surprise statistic.

Perez-Quiros and Sicilia (2002) conduct a similar analysis for the euro area. Policy surprises are measured using principal component analysis for a range of short-term interest rates. They report that more than 80% of ECB policy decisions between 1999 and 2002 had been anticipated by the markets. Repeating this exercise for the United States (using the same sample period), they find that 73% of all FOMC policy decisions were anticipated.

Empirical evidence for the United Kingdom is relatively sparse. Haldane and Read (2000) document the impact of policy rate changes on the UK forward yield curve between 1984 and 1997. They find that about half of policy rate changes are anticipated at the short end. At the long end, they document a greater degree of predictability. Finally, they report that predictability increased after the introduction of the inflation target in October 1992, with the impact of surprises changes falling to about 25% at the short end. Cross-country analysis for the period 1990-97 by the same authors reveals greater predictability of US and German monetary policy, and lower predictability in Italy and the United Kingdom. The authors attribute this to differences in credibility of the respective central banks and related, to differences in the stability of inflationary expectations.

In a separate strand of the literature, Clare and Courtenay (2001) examine the reaction of market interest rates to both macroeconomic announcements and monetary policy decisions. If monetary policy has become more transparent over time, then *ceteris paribus* we would expect market rates to react more to the former, and less to the latter. The event studies, using UK data for the period 1994-99 and 1994-2001, respectively, failed to confirm this hypothesis.

5 Data

Equation **(12)** forms the basis of our empirical work. We are focusing on the ability of the Libor market to predict future values of the Bank of England's 14-day repo rate.[13] Daily data for $y_{14,t}$, the Bank of England's two-week repo rate and four Libor interest rates with maturities of one, three, six and twelve months ($n = \{28, 84, 182, 364\}$) were obtained from Datastream for the period of 1 January 1975 - 26 March 2003.[14]

Four versions of equation **(12)** are adopted:

$$c_{28,t} = \widehat{\beta}_{28} s_{28,t} + \widehat{\alpha}_{28} + \widehat{u}_{28,t} \quad \mathbf{(15)}$$

$$c_{84,t} = \widehat{\beta}_{84} s_{84,t} + \widehat{\alpha}_{84} + \widehat{u}_{84,t} \quad \mathbf{(16)}$$

$$c_{182,t} = \widehat{\beta}_{182} s_{182,t} + \widehat{\alpha}_{182} + \widehat{u}_{182,t} \quad \mathbf{(17)}$$

$$c_{364,t} = \widehat{\beta}_{364} s_{364,t} + \widehat{\alpha}_{364} + \widehat{u}_{364,t} \quad \mathbf{(18)}$$

However, strictly speaking, we can not compute ($s_{28,t}, s_{84,t}, s_{182,t}, s_{364,t}$) because n in equation **(7)** must be a multiple of 14 and our data set consists of daily observations on one-month,

(13) 14 days is the most common maturity of the Bank of England's repos, the central feature of its open market operations since 1997. Prior to 1997, the Bank mainly bought, on an outright basis, bills with a residual maturity of between 1 and 97 days, accompanied from time to time by short-dated repos, primarily in bills. The average maturity of the outright bill purchases varied, but 14 days seems a reasonable assumption.
(14) Datastream codes are: LCBBASE(IR), LDNIB1M(IR), LDNIB3M(IR), LDNIB6M(IR) and LDNIB1Y(IR). Data for the six month Libor rate, LDNIB6M(IR), start on 2 January 1975.

three-month and one-year Libor rates ($y_{30,t}$, $y_{90,t}$, $y_{180,t}$, $y_{360,t}$). We therefore had to rely on the following approximations of the spreads

$$
\begin{aligned}
s_{28,t} &\approx y_{30,t} - y_{14,t} \\
s_{84,t} &\approx y_{90,t} - y_{14,t} \\
s_{182,t} &\approx y_{180,t} - y_{14,t} \\
s_{364,t} &\approx y_{360,t} - y_{14,t}
\end{aligned}
$$

As mentioned earlier, regression standard errors from equations **(15)-(18)** need to be corrected for serial correlation in the expectation errors and we adopt the Newey West procedure, see Newey and West (1987). These corrections, however, do not work well when the degree of serial correlation is large relative to the sample size, see Hodrick (1992). Also, the breakpoint method of Section 6.4 does not seem to work well in the presence of serial correlation in the error terms, see Bai and Perron (2001). For these reasons, we transform the data set of daily observations into a data set of beginning-of-month observations.(15) In other words, equations **(15)-(18)** are implemented by use of monthly data. In doing so, we reduce the amount of serial correlation in the error terms $u_{n,t}$ of **(12)** relative to using daily observations. However, under the assumption of the model in equations **(9)** - **(10)**, serial correlation remains in the residuals of equations **(16)-(18)** in the form of moving average processes with two, five, and eleven lags, respectively. Therefore, the Newey-West procedure mentioned above is implemented by assuming that no serial correlation beyond lags 0, 2, 5, and 11 exist for equations **(15)-(18)** respectively, eg Hodrick (1992).

Before implementing these regressions, it is worth having a preliminary look at the data. Chart 2 displays time series plots of the one-month variables ($c_{28,t}$ and $s_{28,t}$). According to the model in equations **(9)** - **(10)** $s_{28,t}$ and $c_{28,t}$ should move closely together. This seems to be the case in some periods only and mostly after 1995. Charts 3, 4, and 5 display similar time series plot for the three, six, and twelve-month variables ($c_{84,t}$ and $s_{84,t}$, $c_{182,t}$ and $s_{182,t}$, and $c_{364,t}$ and $s_{364,t}$). In all cases, the two variables appear to move closely together in the last third of the sample only.

(15) Specifically, we pick data for the first of each month. If this data point does not exist, eg because the day was in a weekend, we pick data for the last business day of the preceding month.

6 Empirical results

6.1 Estimation of market expectations

Estimates of equations **(15)-(18)** with Newey-West standard errors in brackets are shown in Table B. Note that the effective sample periods differ because of the construction of $c_{n,t}$, see equation **(8)**.

According to the log Expectations Hypothesis β_i should equal unity. However, the $\widehat{\beta}_i$'s in Table B, except for $\widehat{\beta}_{182}$ differ significantly from unity, rejecting the hypothesis at a 5 % significance level. This empirical rejection of the log Expectations Hypothesis is a well-documented result, and has been ascribed to a number of factors. First, it is argued that if the risk premium is time-varying, then equation **(12)** is not correctly specified. Campbell, Shiller and Schoenholtz (1983) suggest that failure to incorporate this time variation into the regression equation could explain the empirical rejection of the log Expectations Hypothesis. This is precisely the motivation for accounting for a time-varying risk premium as reflected in the model described in Section 3.1. Second, Kozicki and Tinsley (2001) provide an alternative explanation. They argue that the empirical model given by equation **(12)** with $\beta_n = 1$ could be rejected by the data even if the log Expectations Hypothesis holds. Instead, the empirical rejection might reflect shifting expectations about the long-term policy objectives of the central bank. In particular, they show that if market participants have imperfect information about the central bank's objectives and are slow in updating their beliefs in the light of new information, then empirical rejection of equation **(12)** is not necessarily evidence against the log Expectations Hypothesis, namely that long bond rates reflect expected short rates.

Table B further shows that the estimates of α_is are negative for $i = \{28, 84, 182\}$ and positive for $i = 364$. Note that α_is can only be interpreted as a linear combination of risk premia, when $\beta_i = 1$ can not be rejected. Hence, the sign of $\widehat{\alpha}_{182}$ is consistent with our priors. We do not have priors on α_i when $\widehat{\beta}_i$ is statistically different from unity, so we only comment on the signs of $\widehat{\alpha}_i$ when $i = 182$.

Finally, Table B shows that the R^2 is quite small for $i = 28$, but increase to $15 - 20\%$ at longer maturities. The fact that predictability is much worse at the one-month maturity might seem counterintuitive, as one might expect arbitrage mechnisms to keep these rates aligned to the policy rate. It is, however, possible that so-called technical factors affect the one-month rate, causing it to provide a poor read of policy rate expectations. These could for example include trades carried out for liquidity management reasons. Residual autocorrelations for equations **(15)-(18)** are displayed in Chart 12. It seems fair to say that no serial correlation exists beyond lags 0, 2, 5, and 11 respectively for equations **(15)-(18)**.

The main question of this paper is whether the ability to predict changes in the Bank of England's two-week repo rate has changed over time. As said earlier, we employ two measures of evaluating the quality of market expectations, σ_u and R^2. Consequently, we will be looking for time variation, in the form of discrete shifts, in these two measures.[16] Changes in predictability, and thereby the risk facing investors, is likely to affect the compensation these investors require for taking positions. In other words, we will also be looking for shifts in α and β, although this is a more indirect way of detecting shifts in predictability (via changes in risk premia) rather than predictability itself (σ_u and R^2).

To examine such time variation, we carry out three sets of tests. First, we re-estimate equations **(15) - (18)**, but allow for a small number of exogenous shifts in (α, β) drawn from our earlier discussion of monetary policy in the United Kingdom (Section 6.2). Second, in Section 6.3, we explore time variation in predictability by visual tools in the form of rolling regressions. Finally, in Section 6.4, we formally test for structural breaks in equations **(15) - (18)** without using any prior information on the location of potential breaks.

6.2 Estimation of market expectations with exogenous regime shifts

In this section, we re-estimate the market expectations from equations **(15) - (18)** by allowing for structural breaks in the relationship between market expectations (yield spreads) and policy rates. These breaks correspond to some of the earlier discussed changes in the monetary policy framework. They include: the introduction of the MTFS (March 1980); the start of ERM membership (October 1990); ERM exit and start of inflation targeting (October 1992) and Bank of England independence (May 1997).

---

(16) Gradual as opposed to discrete shifts in the performance of market expectations might be a more realistic assumption to make, based on the idea that eg learning is a gradual process. However, we proceed with the hypothesis of discrete shifts, mainly due to technical reasons.

Table C below reports Chow test-statistics corresponding to these four breaks, testing for stability jointly in the $\widehat{\alpha}_i$ and $\widehat{\beta}_i$ parameters.[17] They reject the null hypothesis of no breaks for the one-month and twelve-month equations only. However, the null hypothesis will be rejected also for the three-month equation at a significance level of 10 %. Note that the Chow tests employed in Table C do not test for breaks in σ, and hence they may lack power against alternatives where such breaks are taking place.

Table C further reports the estimation results for equations **(15) - (18)**. A number of interesting features stand out. First, in the case of the three, six, and twelve-month rates, the coefficients of determination, R^2s, increase over time, with the period after October 1992 showing a markedly improved fit. Specifically, we find evidence of increased predictability from 1992 onwards, whereas predictability appears to be at its lowest level between 1990 and 1992. For the one-month rate, however, such a rise in predictability is seen only after May 1997.

Second, the root-mean-squared-error of the market forecasts, as embodied in $\widehat{\sigma}_u$, displays a decline over the period, with the lowest estimates observed since November 1992. One could conjecture that this result is driven by the fact that volatility of the target rate has declined over time, see Table A and Chart 1. However the R^2s, measuring the fraction of the total variance of changes in the short rate predicted by the yield spread, have increased as described above. In other words, the predicted variance of the short rate as a fraction of the total variance has increased over time. So the conjecture above seems to be rejected. The bottom line is that the declines in $\widehat{\sigma}_u$, observed in Table C, are consistent with a rise in predictability since 1992.

Third, as a robustness check, predictability as measured by the mean linlin loss criterion is also reported, see $MLL_{0.75}$. The general picture is consistent with $\widehat{\sigma}_u$ and R^2s: predictability has increased since 1992.[18]

Fourth, when estimating equations **(15) - (18)** for the earlier sub-periods, we obtain mixed results. Before 1980, the ability of the market expectations to predict policy rate changes is markedly lower than in the period after 1992 in the case of the three, six, and twelve-month rate, and after 1997 in the case of the one-month rate. After the introduction of the MTFS in March 1980, the

(17) The variance-covariance matrix of the parameters is estimated by the Newey-West method as described in Section 5.
(18) The choice of $b = 0.75$ is arbitrary, but the picture is the same for $b = 0.5$, and for $b = \frac{4}{3}$ and $b = 2$.

markets' ability to predict policy rate changes increases at the twelve-month maturity, but falls at the one, three, and six-month maturities. This is visible in both the $\widehat{\beta}_i$s, the R^2s, and the $\widehat{\sigma}_u$.

As an aside, we re-estimated the market expectations with an additional break, April 1994 (the publication of minutes). While Chow tests confirm this to be a significant break, the regression results, see Table D, show that including 1994 as a break point does not alter the conclusion that the null of no breaks is rejected for all but equation **(18)** at a significance level of 10%. In this case, predictability (as evidenced by the $\widehat{\sigma}_u^2$ and R^2) does not rise until after 1994.

The results presented so far provide a first indication that changes in the UK monetary policy framework were associated with greater predictability in policy making. However, the regression results are not entirely consistent with such a strong conclusion. Increased predictability is not witnessed in all market rates. Moreover, the regression results fluctuate from one sub-period to another, and it is not clear that this is always an accurate reflection of monetary policy. Taken together, these observations point to some of the shortcomings of the chosen method. First, when imposing a small number of break points corresponding to policy changes, the researcher assumes that the policy change in question is immediately incorporated into market expectations. If in contrast, market participants take time to modify their views of central bank behavior, then we would expect to see a gradual adjustment in the behavior of market rates. Regressions that rely on a small number of discrete shifts would not be able to detect this. Second, our choice of four break points was clearly subjective, and we are at risk of having missed other, potentially relevant break dates. In the following two sections, we perform a more objective analysis in the sense that we disregard any prior information on potential break dates and let "data speak for themselves". Finally, it is worth noting that the regressions of this section, as well as those of the following sections, assume parameter stability within each sub-sample.

6.3 Estimation of market expectations based on rolling regressions

In this section, we estimate equations **(15)-(18)** over moving windows of four and eight years.[(19)] Stable coefficient estimates would be associated with no changes in the parameters. Chart 6 displays the results graphically for the four-year window for the one-month rate in row 1, the three-month rate in row 2, the six-month rate in row 3, and the twelve-month rate in the last

(19) Corresponding to windows of 49 and 89 observations.

row.[20] Confidence intervals (95 % significance level) are depicted by dotted lines around the parameter estimates.

For the one-month rate, both $\widehat{\alpha}_{28}$ and $\widehat{\beta}_{28}$ look fairly stable and most of the time they are not significantly different from zero. Moving to the three-month, six-month and twelve-month equations, $\widehat{\alpha}_i$s and $\widehat{\beta}_i$s look fairly unstable. The movements in these parameter estimates are closely related in the sense that they seem to move together. When repeating this exercise with a moving window of eight years (Chart 7), the various parameter estimates are less volatile due to a larger window width but the general impression obtained from Chart 6 continues to hold.

At first sight, Charts 6 and 7 suggest that equations **(15)-(18)** may be subject to structural changes. In particular the $\widehat{\beta}$ coefficients appear more variable during the 1980s and early 1990s. At first sight, this seems to point to a structural break in the early 1990s, and would be consistent with the results of the previous section. But rolling regressions should only be considered as rough visual tools to locate structural breaks. Rigorous identification of structural breaks will be carried out in Section 6.4.

Turning to performance measures of market expectations, Chart 8 displays rolling estimates of the residual standard error $\widehat{\sigma}_n$ with a moving window of four years. Chart 9 displays the same content with a moving window of eight years. The general picture is very clear. Expected loss from market expectations, measured by the RMSE, declined gradually over the period, with the exception of 1980-82 for the four-year window.

Chart 10 displays R^2s from the regressions of Chart 6 with a moving window of four years of observations, R^2_{28} referring to R^2 from equation **(15)**, R^2_{84} to R^2 from equation **(16)**, R^2_{182} to R^2 from equation **(17)**, and R^2_{364} to R^2 from equation **(18)**, respectively. The charts indicate substantial variation over time in the R^2s, and they are noticeably higher from the mid-1990s onwards probably due to sterling's exit from ERM in 1992. R^2_{28} ranges between 0 and 0.15 until 1997 where it spikes up and stays between 0.1 and 0.3 until the end of the sample. R^2_{84} rises above 0.5 after 1995, having been below 0.3 during most of the preceding years, and even close to zero for prolonged periods of time. The plots of R^2_{182} and R^2_{364} are similar, reaching highs of 0.4 around 1985 and 0.6 around 1990. From 1995 onwards, the measures are consistently around 0.6. Note

(20) The time index of the parameter estimates denote the centre of the moving window. Eg the very first $\widehat{\beta}_{28}$ in row 1 of Chart 6 corresponds to January 1977 and is estimated over the sample period of Jan 1975 to Jan 1979.

the strong comovement between R^2_{84}, R^2_{182} and R^2_{364}, which was also observed in Charts 6 and 8. For reference, Chart 11 displays rolling R^2s with the larger moving window. The general picture stays the same. But once again, one has to be careful in interpreting these plots in the sense that the evidence of structural breaks is based purely on visual tools. Furthermore, in the absence of standard errors for the R^2s, it is hard to gauge the exact change in R^2s or whether the observed changes in predictability were statistically significant.

Nonetheless, it is interesting to compare the results obtained so far with those of Lange, Sack and Whitesell (2003). They carry out rolling regressions using three-month Treasury bill rates and report a significant increase in the R^2s in the late 1980s and a further rise in the early 1990s. R^2's rise from around zero in the early 1980s to well above 0.7 in early 1994. The authors argue that these rises seem to coincide with improvements in Federal Reserve policy transparency.

6.4 Estimation of market expectations based on the Bai-Perron method

In this section, we carry out a more rigorous analysis of time variation in predictability by employing the method of Jushan Bai and Pierre Perron. The core theory is described Bai and Perron (1998), numerical issues and software are described in Bai and Perron (2003a), a simulation study with practical recommendations can be found in Bai and Perron (2001), and Bai and Perron (2003b) provide additional critical values for the tests derived in Bai and Perron (1998). The Bai and Perron method has recently been applied by Carlson, Craig and Schwarz (2000) on M2 velocity and by Carlson, Pelz andWohar (2002) on equity valuation.

6.4.1 Breakpoint method

The modelling framework is a generalisation of equation **(12)**, allowing for breaks in the parameters

$$c_{n,t} = \beta_{n,j} s_{n,t} + \alpha_{n,j} + u_{n,t} \text{ for } t = T_{j-1} + 1, ..., T_j \text{ and } T_0 = 0, T_{m+1} = T \qquad \mathbf{(19)}$$

where T is the sample size and m is the number of breaks. So $(\beta_{n,1}, \alpha_{n,1})$ correspond to the parameters for the first segment $[0 : T_1]$, $(\beta_{n,2}, \alpha_{n,2})$ correspond to the parameters for the second segment $[T_1 + 1 : T_2]$, etc. The aim of this section is to estimate $\{T_1, T_2, ..., T_m\}$ and the associated parameters

$$(\beta_{n,j}, \alpha_{n,j}) \text{ for } j = 1, 2, .., k$$

We have chosen the method of Bai and Perron (1998) primarily due to three unique features. In particular, it allows for

- Multiple structural changes.
- General forms of serial correlation and heteroskedasticity in the errors.
- Different distributions for the errors and the regressors across segments.

Allowing for multiple structural changes is crucial because there are several potential break dates over the sample period.[(21)] The reasons mentioned in the last two bullet points are important because shifts in the ability to anticipate interest rate changes are likely to be associated with other shifts in the parameters of the model, in particular the variance of the error term.

A detailed description of the method and its implementation is beyond the scope of this paper. Instead we provide a brief introduction to the implementation of the tests.[(22)] Broadly speaking, all tests consist of estimating equation **(19)** repeatedly with all combinations of breakpoints $\{T_1, T_2, ..., T_m\}$ and choosing the set of breakpoints that minimise the sum of squared residuals. There are three categories of tests, all using this same basic idea:

- **Test 1**: **Test of no break versus a fixed number of breaks (l)**

  $$H_0 : \text{No breaks} \qquad H_A : l \text{ breaks, where } l > 0$$

  This test consist of estimating **(19)** repeatedly for $m = 1 \,...l$. Doing so, one obtains a sequence of F-statistics, which in turn are used to compute a summary test statistic: $SupF_T(l)$. The test rejects for large values of $SupF_T(l)$ and is derived in Section 4.1 of Bai and Perron (1998). Selection of l will be clarified below.
- **Test 2**: **Test of no structural break versus an unknown number of breaks bounded from above by M.**

  $$H_0 : \text{No breaks} \qquad H_A : \text{Number breaks between 1 and } M.$$

  As in Test 1, a sequence of F-statistics are computed and combined into a summary F-test statistic. In turn, these are put together, using some fixed weights determined by the researcher.

(21) See the discussion in Section 2.
(22) Technical details of the analysis which would allow the reader to replicate our results are available upon request.

Hence, the name 'double maximum'. Following default settings in the software related to Bai and Perron (2003a), we set $M = 5$.There are two versions of this test, the simple double maximum test

$$UDmax$$

and a variant[23] denoted by

$$WDMax$$

They differ in the choice of weights. Computation of the $WDMax$ test statistic depends on the chosen significance level, so $WDMax^{(a\%)}$ denotes the test statistic associated with a significance level of a%. Both tests reject for large values of $UDmax/WDMax^{(a\%)}$. For more detailed information, the reader is referred to Section 4.2 of Bai and Perron (1998).

- **Test 3**: **Test of l breaks against the alternative of one additional break ($l + 1$)**

$$H_0 : l \text{ breaks} \qquad H_A : l + 1 \text{ breaks}$$

To conduct this test, **(19)** is estimated sequentially for increasing l, with the summary test statistic denoted by $SupF_T(l + 1|l)$. The test rejects for large values of $SupF_T(l + 1|l)$ and is derived in Section 4.3 of Bai and Perron (1998). Clearly, Test 1 and Test 3 intersect for $l = 0$.

Having defined the various statistical tests used to identify breakpoints, T_m in **(19)**, we now describe the actual implementation. The question is: how should we combine Tests 1, 2 and 3 to estimate the number of breakpoints m and the associated locations $\{T_1, T_2, ..., T_m\}$?

The recommended estimation strategy of Bai and Perron (1998), denoted by the *sequential procedure*, is to start by setting l to a small number of breaks (typically zero). This procedure then tests sequentially the null of l breaks versus the alternative hypothesis of $l + 1$ breaks by applying $SupF_T(l + 1|l)$ (Test 3) sequentially from $l = 0$ (i.e. Test 1) until the test fails to reject the null hypothesis of no additional breakpoints. However, in a simulation study, Bai and Perron (2001) highlight a potential shortcoming of this procedure. In particular, in the presence of multiple breaks, mechanical application of the above mentioned strategy may be sub-optimal in the sense that the selected number of breaks tends to be too low.[24]

For this reason, Bai and Perron (2001) recommend an alternative procedure - in what follows

(23) This test should have higher power compared to $UDmax$ in the presence of a large number of breaks.
(24) The reason being that if eg two breaks are present, the first test in the sequential procedure $F_T(1|0)$ tends to accept the null of no breaks.

referred to as *preferred procedure*. This procedure is motivated by their simulation results that show how it often is more difficult to distinguish between no break and a single break than between no break and multiple breaks, when in fact multiple breaks are present. Bearing this in mind, the first step of the preferred procedure consists of conducting the double maximum tests to see if at least one break is present (Test 2). Bai and Perron (2001) show that in finite samples, these tests have greater power than the test of no change versus a fixed number of breaks (Test 1), which is the first step in the sequential procedure. If the double maximum tests indicate the presence of at least one break, then one can apply $SupF_T(l+1|l)$ (Test 3) sequentially from a suitable choice of l, but avoiding $l=0$. To determine l, Test 1 is employed, in the sense that the first significant value of $SupF_T(1)$, $SupF_T(2)$, $SupF_T(3)$, $SupF_T(4)$, $SupF_T(5)$ determines l.(25)

We report the results of both procedures but attach most weight to the *preferred procedure* following Bai and Perron (2001)'s recommendations. Computations are performed in GAUSS 5.0 by the software(26) of Pierre Perron.(27)

6.4.2 Breakpoint results

Tables E, F, G and H present empirical results for equations **(15)**, **(16)**, **(17)**, **(18)**, respectively. The first section of the tables, *Specification*, defines the model. Note that T_i denotes the end point of segment i. Test statistics for the tests $F_T(l)$, $UDmax/WDMax$, and $F_T(l+1|l)$ are displayed in the second panel, named *Tests*. Rejection of the null hypothesis at 5% and 1% significance levels are denoted by * and **, respectively. *Number and location of breaks selected* summarises the number and locations of breaks according to two estimation strategies: The *sequential procedure* described above and the *preferred procedure* of Bai and Perron (2001). The final panel of the tables displays the estimated model selected by the *preferred procedure*. Standard errors in brackets are provided below coefficient estimates. R_j^2 denotes the coefficient of determination for the sub model corresponding to $t = T_{j-1}+1, ..., T_j$. Estimates of breakpoints T_i are displayed in the last row. Confidence intervals with coverage probability of 95% are provided below.

(25) The selection of a suitable choice of l is not specified in Bai and Perron (2001), so the selection process outlined above is our invention.
(26) Available at *http://www.econ.queensu.ca/jae/2003-v18.1/bai-perron/*
(27) We discovered a bug in the software, version 2.4 November 19 1999, in relation to estimating models with a fixed number of breaks ($estimfix = 1$). Corrected code can be obtained upon request.

For the one-month rate, Table E shows that the number of breaks is zero[(28)] according to the *sequential procedure*. However, the *preferred procedure* selects two[(29)] breaks: Jan 1980 and Mar 1984. The estimated βs are insignificant, except for the first segment, and R^2s are declining over the period. In contrast, the $\widehat{\sigma}_{28,i}$s are declining over the period, so the two measures of forecast performance yield different results. Table F presents the results for the three-month rate. The *preferred procedure* picks four[(30)] breakpoints: January 1980, March 1984, October 1989 and December 1993. Predictability, as measured by R^2 and $\widehat{\sigma}_{84,i}$, attains a maximum in the last sub-sample (Jan 1994-Mar 2003). The results for the six and twelve-month rates in Tables G and H are similar in the sense that both the *sequential* and the *preferred procedure* indicate no breakpoints.

Confidence intervals for the breakpoints are wide in Tables E to H and typically cover several years. In other words, the point estimates are associated with a large degree of uncertainty. When allowing for these margins of errors, it might, however, be easier to see the economic relevance of the estimated breakpoints. The first breakpoint, January 1980, comes a few months before the announcement of the MTFS. As explained earlier, the MTFS was at the time viewed as an critical improvement on previous policies. The second break point, March 1984, is more difficult to explain, even when taking into account its confidence interval (which is so wide in the case of the three-month rate that it includes the first breakpoint). October 1989 comes up as a third breakpoint, but only in the three-month regression. That month saw one of the larger policy rate increases - 100 basis points coming on the heel of a similar rate rise by the Bundesbank - but it is unclear why this should produce a structural break in the expectations model (the United Kingdom had been shadowing the DM since 1987), and why this shows up only in the three-month regression. The final breakpoint, December 1993, is present in the three-month equation only and might reflect the October 1992 change. It could also be related to increased transparency about monetary policy decision making following the introduction of the *Inflation Report* in February 1993. Unfortunately, the software failed to produce a confidence interval in this case due to numerical problems.

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(28) The idea of the sequential procedure is to test sequentially the null of n breaks vs the alternative hypothesis of $n+1$ breaks, starting from $n=0$. So the first test to consider is the test of zero breaks vs one break: $SupF_T(1) = 8.99$. It turns out that it does not reject the null of zero breaks.
(29) $UDmax/WDmax$ tests indicate the presence of at least one break. Hence, we jump to the first significant $SupF_T()$, which is $SupF_T(2)$. Testing the null of two breaks vs three breaks by $SupF_T(3|2)$ does not reject the null.
(30) $UDmax/WDmax$ tests indicate the presence of at least one break. Hence, we jump to the first significant $SupF_T()$, which is $SupF_T(4)$. Testing the null of four breaks vs five breaks by $SupF_T(5|4)$ does not reject the null.

It is interesting to note that on the whole, the data do not select the earlier-used exogenous breakpoints. This could be interpreted in three, not necessarily competing ways. First, the power properties of the Bai Perron method are unknown, when the number of breaks is larger than two, see Bai and Perron (2001). As suggested in Section 2, there may be multiple structural breaks in our regression equations, and therefore the method may very well have low power against the alternative of multiple breaks. Second, the simulation study by Bai and Perron (2001), shows that serial correlation in the error term induces a loss of power in detecting breaks. Combining this with the fact that the *preferred procedure* estimates 2, 4, 0 and 0 breakpoints, respectively for equations **(15) - (18)**, one could hypothesise that failure to detect breaks in the six and twelve-month equations, **(17) - (18)**, is due to the presence of strong residual autocorrelation in these equations. Third, the Bai Perron method is designed to pick up discrete shifts in parameters. If in fact, market participants are slow to adjust to changes, eg through a dynamic learning process, then more gradual parameter changes would be expected. Consequently, the Bai Perron method might not detect these gradual breakpoints.

6.5 Specification tests

The purpose of this section is to explore whether the models of interest rate expectations in equations **(15) - (18)** are well specified, in the sense that the statistical restrictions implied by the models are reflected in the data. In particular, we focus on two restrictions:

- Restriction on serial correlation of error term. Serial correlation is allowed up to lag orders of 0, 2, 5 and 11 for equations **(15) - (18)** respectively, see Section 5.
- Zero coefficients on lagged changes in the Bank of England two-week repo rate in the regressions **(15) - (18)**.

Autocorrelation functions for equations **(15) - (18)** are displayed graphically in Chart 12. It seems fair to say that the restriction on residual autocorrelation in the form of maximum lag orders of 0, 2, 5 and 11 is fulfilled.

The second restriction is a special case of the more general restriction that the spread s_t contains all relevant information about market expectations. Therefore any additional current (and lagged) variables in **(12)** should be insignificant. A good candidate for a variable with potential explanatory power in equation **(12)** is the change in the Bank of England's two-week repo rate. Chart 1, which was shown earlier, clearly indicates that changes in the policy rate are highly persistent in the sense that increases/decreases tend to be followed by increases/decreases. Therefore, we estimate the following regressions , allowing for changes in dynamics corresponding to the exogenous breaks identified in Section 6.2.

$$c_{28,t} = \phi'_{28,j} b_t + \phi''_{28,j} b_{t-1} + \phi'''_{28,j} b_{t-2} + w_{28,t} \qquad \text{for } t = T_{j-1}+1, ..., T_j \tag{20}$$

$$c_{84,t} = \phi'_{84,j} b_t + \phi''_{84,j} b_{t-1} + \phi'''_{84,j} b_{t-2} + w_{84,t} \qquad \text{for } t = T_{j-1}+1, ..., T_j \tag{21}$$

$$c_{182,t} = \phi'_{182,j} b_t + \phi''_{182,j} b_{t-1} + \phi'''_{182,j} b_{t-2} + w_{182,t} \qquad \text{for } t = T_{j-1}+1, ..., T_j \tag{22}$$

$$c_{364,t} = \phi'_{364,j} b_t + \phi''_{364,j} b_{t-1} + \phi'''_{364,j} b_{t-2} + w_{364,t} \qquad \text{for } t = T_{j-1}+1, ..., T_j \tag{23}$$

$$b_t = y_{14,t} - y_{14,t-30} \tag{24}$$

The purpose of this exercise is to explore whether lagged base rate changes have any explanatory power for the variables $c_{28,t}$, $c_{84,t}$, $c_{182,t}$ and $c_{364,t}$. If that is the case, b_t provides a good candidate for testing the specifications **(15) - (18)**. The results (available upon request) indicate that b_t, b_{t-1}, b_{t-2} do have explanatory power for $c_{28,t}$, $c_{84,t}$, $c_{182,t}$ and $c_{364,t}$. In order to reduce the number of estimated coefficients, we estimate equations **(15) - (18)** with just current values of b_t as an additional variable, see upper section of Table I, for each of the segments identified in Section 6.2. The lower panel of this table displays the results. Only $\widehat{\phi}_{28,j}$ appears to be significantly different from zero, so it seems plausible to conclude that the models of expectations formation in equations **(15) - (18)** are well-specified.

7 Concluding remarks

Our prior when embarking on this project was that increased stability in policy rate setting (as evidenced in Table A), together with increased transparency of monetary policy decision making would have contributed to increased ability of market interest rates to predict future policy rate changes. In particular, following recent US evidence, we were interested in identifying structural breaks in the relationship between market and policy rates following key changes in the monetary policy framework of the United Kingdom. Our evidence on such structural change has proved very mixed.

First, we find that in the context of a simple expectations model, exogenous breakpoints corresponding to key policy changes are indeed significant. Moreover, we find that predictability has improved over time, with the expectations model providing a decidedly better fit after the introduction of inflation targeting in October1992.

But closer examination of the data reveals that things are not that clear-cut. First, when examining different maturities, we see that the results do no always generalise. For example, predictability from the shortest rates did not increase markedly until after May 1997. Second, our tests showed that while predictability did indeed change over time, these changes were not necessarily concentrated around the exogenous breakpoints suggested by the history of policy reforms. Instead, predictability varied widely across the sample period. For example, at the longest horizon, it rose briefly after the introduction of the MTFS in March 1980 and plummeted after sterling's exit from the ERM in October 1990. Rolling regressions show that in the 1980s and early 1990s predictability fluctuated between 0 and 60%, with frequent highs and lows seemingly unrelated to any policy changes. Attempts to identify structural breakpoints in a formal way were on the whole unsuccessful. Nonetheless, over the longer sample period (1975-2003), the data show a clear improvement in the ability of market rates to anticipate policy changes.

Tables and charts

Table A: Policy rate changes (1975-2003)

	Jan 75 - Oct 85	Nov 85 - Sep 92	Oct 92 - April 97	May 97 - Mar 03
Total number of changes	88	41	13	24
Number of rises	31	16	4	10
Number of cuts	57	25	9	14
Number of reversals	24	12	3	3
Distribution of rate changes				
-2	2	1		
-1	9	3	3	
-0.75	2			
-0.5	40	21	1	4
-0.25	4		5	10
0.125	2			
0.25	2		1	10
0.5	5	8	3	
0.75	1			
1	9	7		
1.5	6	1		
2	5			
3	1			

Table B: Estimates of equations (15)-(18) for the full sample

	$\widehat{\alpha}_i$	$\widehat{\beta}_i$	R^2	Sample period
$i=28$	-0.01 (0.01)	0.05 (0.03)	0.01	Jan 1975 - Mar 2003
$i=84$	-0.10 (0.04)	0.52 (0.09)	0.16	Jan 1975 - Jan 2003
$i=182$	-0.15 (0.09)	0.76 (0.12)	0.20	Feb 1975 - Oct 2002
$i=364$	0.12 (0.06)	0.70 (0.10)	0.15	Jan 1975 - Apr 2002

Table C: Chow tests of four breakpoints and associated parameter estimates

Chow tests of breakpoints at Mar 80, Oct 90, Oct 92, and May 97

	Equation **(15)**	Equation **(16)**	Equation **(17)**	Equation **(18)**
Test statistic	1.98*	14.93	10.98	24.85**
P-value	0.05	0.06	0.20	0.00

Associated parameter estimates

	[Jan75-Mar80]	[Apr80-Oct90]	[Nov90-Oct92]	[Nov92-May97]	[Jun97-]
$\widehat{\alpha}_{28,j}$	0.03	0.00	-0.07	-0.01	-0.01
$\widehat{\beta}_{28,j}$	0.15	-0.06	0.22	-0.06	0.27
R_j^2	0.10	0.01	0.09	0.01	0.18
$\widehat{\sigma}_{28,j}$	0.31	0.26	0.10	0.10	0.08
$MLL_{0.75}$	0.18	0.11	0.07	0.04	0.05
$\widehat{\alpha}_{84,j}$	0.07	-0.18	-0.31	-0.06	-0.11
$\widehat{\beta}_{84,j}$	0.61	0.51	-0.15	0.60	0.67
R_j^2	0.24	0.11	0.02	0.35	0.52
$\widehat{\sigma}_{84,j}$	0.75	0.66	0.34	0.18	0.15
$MLL_{0.75}$	0.51	0.40	0.23	0.11	0.10
$\widehat{\alpha}_{182,j}$	0.17	-0.20	-0.80	-0.13	-0.25
$\widehat{\beta}_{182,j}$	0.82	0.71	-0.05	0.80	0.96
R_j^2	0.19	0.17	0.00	0.67	0.66
$\widehat{\sigma}_{182,j}$	1.27	0.97	0.63	0.23	0.24
$MLL_{0.75}$	0.89	0.66	0.44	0.16	0.16
$\widehat{\alpha}_{364,j}$	0.89	0.22	-1.28	-0.01	-0.34
$\widehat{\beta}_{364,j}$	0.28	0.90	-0.13	0.72	1.03
R_j^2	0.02	0.25	0.01	0.64	0.61
$\widehat{\sigma}_{364,j}$	2.11	1.31	0.90	0.37	0.42
$MLL_{0.75}$	1.46	0.92	0.65	0.27	0.28

Table D: Chow tests of five breakpoints and associated parameter estimates

Chow tests of breakpoints at Mar 80, Oct 90, Oct 92, Apr 94, and May 97

	Equation **(15)**	Equation **(16)**	Equation **(17)**	Equation **(18)**
Test statistic	1.66	21.61*	11.57	26.92**
P-value	0.09	0.02	0.31	0.00

Associated parameter estimates

	[Jan75-Mar80]	[Apr80-Oct90]	[Nov90-Oct92]	[Nov92-Apr94]	[May94-May97]	[Jun97-]
$\widehat{\alpha}_{28,j}$	0.03	0.00	−0.07	−0.04	0.02	−0.01
$\widehat{\beta}_{28,j}$	0.15	−0.06	0.22	−0.15	0.03	0.27
R_j^2	0.10	0.01	0.09	0.06	0.01	0.18
$\widehat{\sigma}_{28,j}$	0.31	0.26	0.10	0.12	0.08	0.08
$MLL_{0.75}$	0.18	0.11	0.07	0.05	0.04	0.05
$\widehat{\alpha}_{84,j}$	0.07	−0.18	−0.31	−0.13	−0.04	−0.11
$\widehat{\beta}_{84,j}$	0.61	0.51	−0.15	0.30	0.59	0.67
R_j^2	0.24	0.11	0.02	0.05	0.48	0.52
$\widehat{\sigma}_{84,j}$	0.75	0.66	0.34	0.25	0.13	0.15
$MLL_{0.75}$	0.51	0.40	0.23	0.16	0.09	0.10
$\widehat{\alpha}_{182,j}$	0.17	−0.21	−0.80	−0.11	−0.15	−0.24
$\widehat{\beta}_{182,j}$	0.82	0.71	−0.06	0.88	0.82	0.96
R_j^2	0.19	0.17	0.00	0.37	0.71	0.66
$\widehat{\sigma}_{182,j}$	1.27	0.97	0.63	0.31	0.18	0.24
$MLL_{0.75}$	0.89	0.66	0.44	0.20	0.13	0.16
$\widehat{\alpha}_{364,j}$	0.89	0.22	−1.28	0.10	−0.04	−0.34
$\widehat{\beta}_{364,j}$	0.28	0.90	−0.13	0.96	0.73	1.03
R_j^2	0.02	0.25	0.01	0.52	0.57	0.61
$\widehat{\sigma}_{364,j}$	2.11	1.31	0.90	0.36	0.37	0.42
$MLL_{0.75}$	1.46	0.92	0.65	0.25	0.28	0.28

Table E: Estimates of structural changes in equation (15)

		Specification		
$c_{28,t} = \beta_{28,j} s_{28,t} + \alpha_{28,j} + u_{28,t}$		for $t = T_{j-1}+1, ..., T_j$ $\quad T_0 = 0$ and $T_{m+1} = T$ where T is the sample size and m is the number of breaks		
		Tests		
$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$
8.99	16.83**	11.61**	9.20**	9.07**
$UDmax$	$WDmax^{(5\%)}$	$WDmax^{(1\%)}$		
16.83**	19.80(*)	21.30(**)		
$SupF_T(2\|1)$	$SupF_T(3\|2)$	$SupF_T(4\|3)$	$SupF_T(5\|4)$	
2.22	4.36	1.26	6.53	
		Number and location of breaks selected		
Sequential procedure	0	{}		
Preferred procedure	2	$\{Jan80, Mar84\}$		
		Parameter estimates with two breaks		
$\widehat{\alpha}_{28,1}$	$\widehat{\alpha}_{28,2}$	$\widehat{\alpha}_{28,3}$		
0.04	−0.14**	0.00		
(0.06)	(0.03)	(0.01)		
$\widehat{\beta}_{28,1}$	$\widehat{\beta}_{28,2}$	$\widehat{\beta}_{28,3}$		
0.17**	0.09	0.02		
(0.06)	(0.07)	(0.20)		
$\widehat{\sigma}_{28,1}$	$\widehat{\sigma}_{28,2}$	$\widehat{\sigma}_{28,3}$		
0.32	0.20	0.18		
R_1^2	R_2^2	R_3^2		
0.11	0.05	0.00		
$\widehat{T}_1$	$\widehat{T}_2$			
Jan 1980	Mar 1984			
[Jun 1979 : Aug 1985]	[Apr 1983 : Oct 1985]			

Table F: Estimates of structural changes in equation (16)

Specification				
$c_{84,t} = \beta_{84,j} s_{84,t} + \alpha_{84,j} + u_{84,t}$		for $t = T_{j-1}+1, ..., T_j$ $\quad T_0 = 0$ and $T_{m+1} = T$ where T is the sample size and m is the number of breaks		
Tests				
$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$
1.75	6.05	6.98	34.27^{**}	51.70^{**}
$UDmax$	$WDmax^{(5\%)}$	$WDmax^{(1\%)}$		
51.70^{**}	$101.37^{(*)}$	$113.52^{(**)}$		
$SupF_T(2\|1)$	$SupF_T(3\|2)$	$SupF_T(4\|3)$	$SupF_T(5\|4)$	
5.95	7.84	2.37	7.80	
Number and location of breaks selected				
Sequential procedure	0	{}		
Preferred procedure	4	$\{Jan80, Mar84, Oct89, Dec93\}$		
Parameter estimates with four breaks				
$\widehat{\alpha}_{84,1}$	$\widehat{\alpha}_{84,2}$	$\widehat{\alpha}_{84,3}$	$\widehat{\alpha}_{84,4}$	$\widehat{\alpha}_{84,5}$
0.09	-0.54^{*}	-0.03	-0.22^{**}	-0.08
(0.19)	(0.29)	(0.03)	(0.08)	(0.06)
$\widehat{\beta}_{84,1}$	$\widehat{\beta}_{84,2}$	$\widehat{\beta}_{84,3}$	$\widehat{\beta}_{84,4}$	$\widehat{\beta}_{84,5}$
0.67^{**}	0.57^{**}	1.15	0.11	0.66^{*}
(0.18)	(0.27)	(0.70)	(1.51)	(0.35)
$\widehat{\sigma}_{84,1}$	$\widehat{\sigma}_{84,2}$	$\widehat{\sigma}_{84,3}$	$\widehat{\sigma}_{84,4}$	$\widehat{\sigma}_{84,5}$
0.75	0.49	0.68	0.31	0.15
R_1^2	R_2^2	R_3^2	R_4^2	R_5^2
0.26	0.33	0.22	0.01	0.51
$\widehat{T}_1$	$\widehat{T}_2$	$\widehat{T}_3$	$\widehat{T}_4$	
Jan 1980	Mar 1984	Oct 1989	Dec 1993	
[Jun 1978 : Oct 1985]	[Mar 1980 : Aug 1984]	Not available	Not available	

Table G: Estimates of structural changes in equation (17)

Specification				
$c_{128,t} = \beta_{128,j} s_{128,t} + \alpha_{128,j} + u_{128,t}$	for $t = T_{j-1}+1, ..., T_j$ $T_0 = 0$ and $T_{m+1} = T$ where T is the sample size and m is the number of breaks			
Tests				
$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$
1.38	4.98	4.45	3.28	3.88
$UDmax$	$WDmax^{(5\%)}$	$WDmax^{(1\%)}$		
4.98	7.62	8.53		
$SupF_T(2\|1)$	$SupF_T(3\|2)$	$SupF_T(4\|3)$	$SupF_T(5\|4)$	
7.40	4.81	0.73	3.26	
Number and location of breaks selected				
Sequential procedure	0	{}		
Preferred procedure	0	{}		
Parameter estimates with no breaks				
$\widehat{\alpha}_{182,1}$				
-0.15				
(0.09)				
$\widehat{\beta}_{182,1}$				
0.76				
(0.12)				
$\widehat{\sigma}_{182,1}$				
0.86				
R_1^2				
0.20				

Table H: Estimates of structural changes in equation (18)

		Specification		
$c_{364,t} = \beta_{364,j} s_{364,t} + \alpha_{364,j} + u_{364,t}$	for $t = T_{j-1}+1, ..., T_j$ $T_0 = 0$ and $T_{m+1} = T$ where T is the sample size and m is the number of breaks			
		Tests		
$SupF_T(1)$	$SupF_T(2)$	$SupF_T(3)$	$SupF_T(4)$	$SupF_T(5)$
0.38	4.41	3.66	2.83	2.53
$UDmax$	$WDmax^{(5\%)}$	$WDmax^{(1\%)}$		
4.41	5.19	5.58		
$SupF_T(2\|1)$	$SupF_T(3\|2)$	$SupF_T(4\|3)$	$SupF_T(5\|4)$	
1.24	0.91	0.91	1.36	
		Number and location of breaks selected		
Sequential procedure	0	{}		
Preferred procedure	0	{}		
		Parameter estimates with no breaks		
$\widehat{\alpha}_{364,1}$				
0.12				
(0.06)				
$\widehat{\beta}_{364,1}$				
0.70**				
(0.10)				
$\widehat{\sigma}_{364,1}$				
1.37				
R_1^2				
0.15				

Table I: Specification tests of equations (15) - (18)

Specification

$$\left.\begin{aligned} c_{28,t} &= \widehat{\beta}_{28,j} s_{28,t} + \widehat{\alpha}_{28,j} + \widehat{\phi}_{28,j} b_t + \widehat{u}_{28,t} \\ c_{84,t} &= \widehat{\beta}_{84,j} s_{84,t} + \widehat{\alpha}_{84,j} + \widehat{\phi}_{84,j} b_t + \widehat{u}_{84,t} \\ c_{182,t} &= \widehat{\beta}_{182,j} s_{182,t} + \widehat{\alpha}_{182,j} + \widehat{\phi}_{182,j} b_t + \widehat{u}_{182,t} \\ c_{364,t} &= \widehat{\beta}_{364,j} s_{364,t} + \widehat{\alpha}_{364,j} + \widehat{\phi}_{364,j} b_t + \widehat{u}_{364,t} \end{aligned}\right\} \text{for } t = T_{j-1}+1, \ldots., T_j$$

Parameter estimates

	[Jan75-Mar80]	[Apr80-Oct90]	[Nov90-Oct92]	[Nov92-May97]	[Jun97-]
$\widehat{\alpha}_{28,j}$	0.02	0.00	-0.09	0.01	-0.01
$\widehat{\beta}_{28,j}$	0.13	-0.06	0.22	0.06	0.18
$\widehat{\phi}_{28,j}$	0.07**	-0.01	-0.06	0.14	0.18
$\widehat{\alpha}_{84,j}$	0.08	-0.18	-0.25	-0.04	-0.09
$\widehat{\beta}_{84,j}$	0.60	0.51	-0.26	0.57	0.53
$\widehat{\phi}_{84,j}$	0.07	0.00	0.23	0.28	0.32
$\widehat{\alpha}_{182,j}$	0.17	-0.21	-0.74	-0.12	-0.25
$\widehat{\beta}_{182,j}$	0.80	0.71	-0.13	0.75	0.96
$\widehat{\phi}_{182,j}$	0.06	-0.07	0.26	0.14	0.02
$\widehat{\alpha}_{364,j}$	0.90	0.22	-1.29	-0.02	-0.40
$\widehat{\beta}_{364,j}$	0.33	0.89	-0.12	0.74	1.20
$\widehat{\phi}_{364,j}$	0.19	-0.08	-0.07	-0.09	-0.68

In this table we focus on the significance of the ϕ-coefficients. The null of $\phi = 0$ is tested for each ϕ-coefficient, and a rejection of this hypothesis at a one/five significance level is denoted by **/*, respectively. Standard errors are estimated by the Newey-West method allowing for serial correlation up to lag order 0, 2, 5, and 11 for the equations.

Chart 1: UK policy rates (1975-2003)

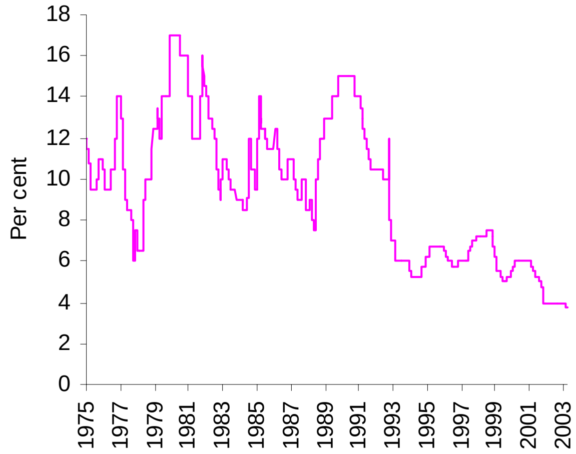


Chart 2: Time series plot of $c_{28,t}$ and $s_{28,t}$

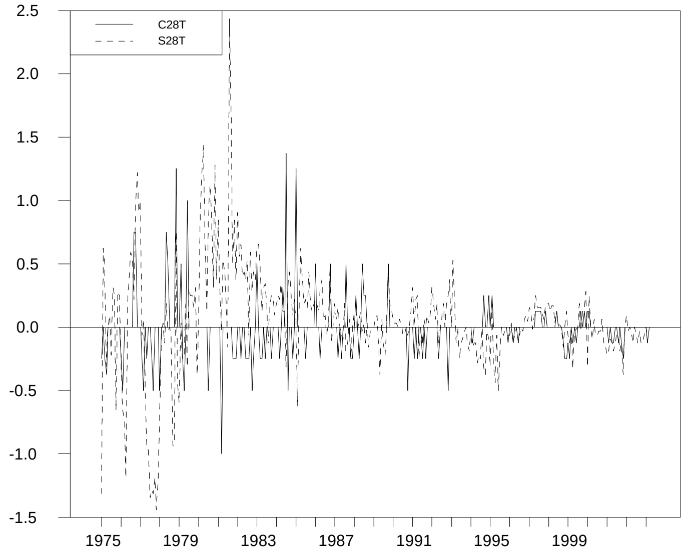


Chart 3: Time series plot of $c_{84,t}$ and $s_{84,t}$

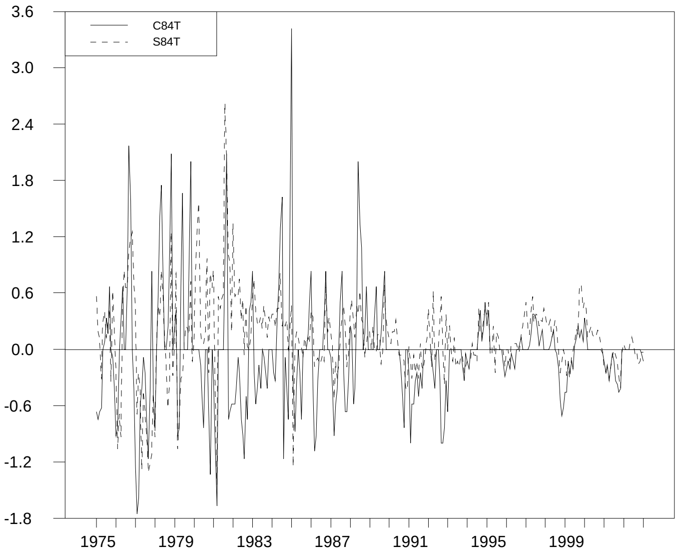


Chart 4: Time series plot of $c_{182,t}$ and $s_{182,t}$

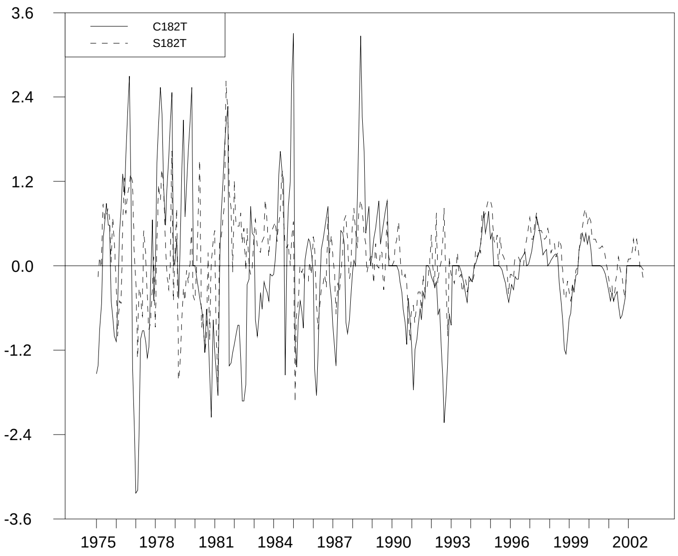


Chart 5: Time series plot of $c_{364,t}$ and $s_{364,t}$

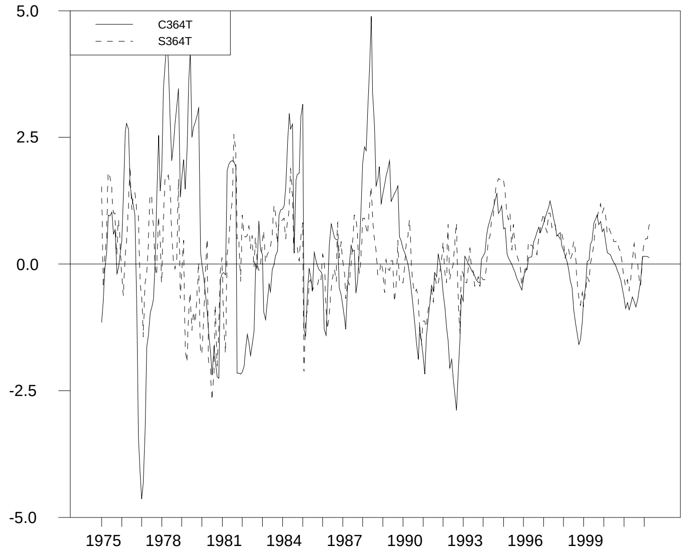
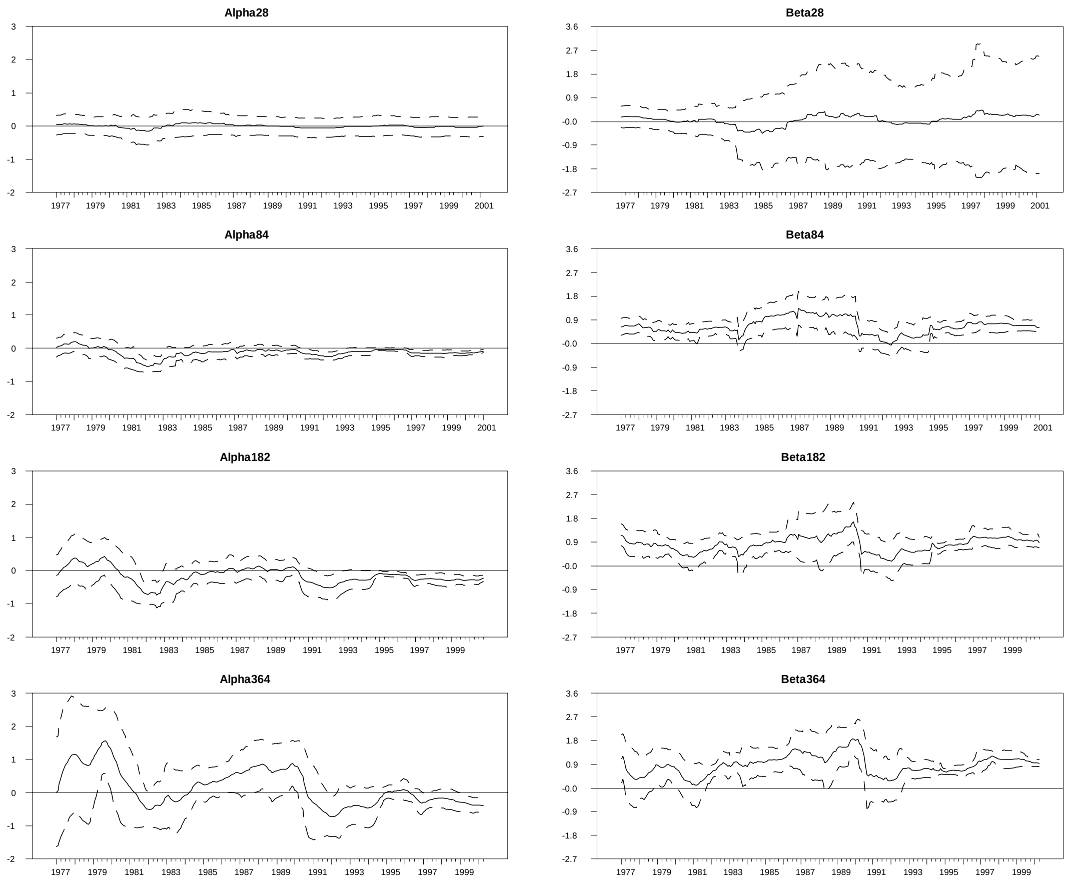
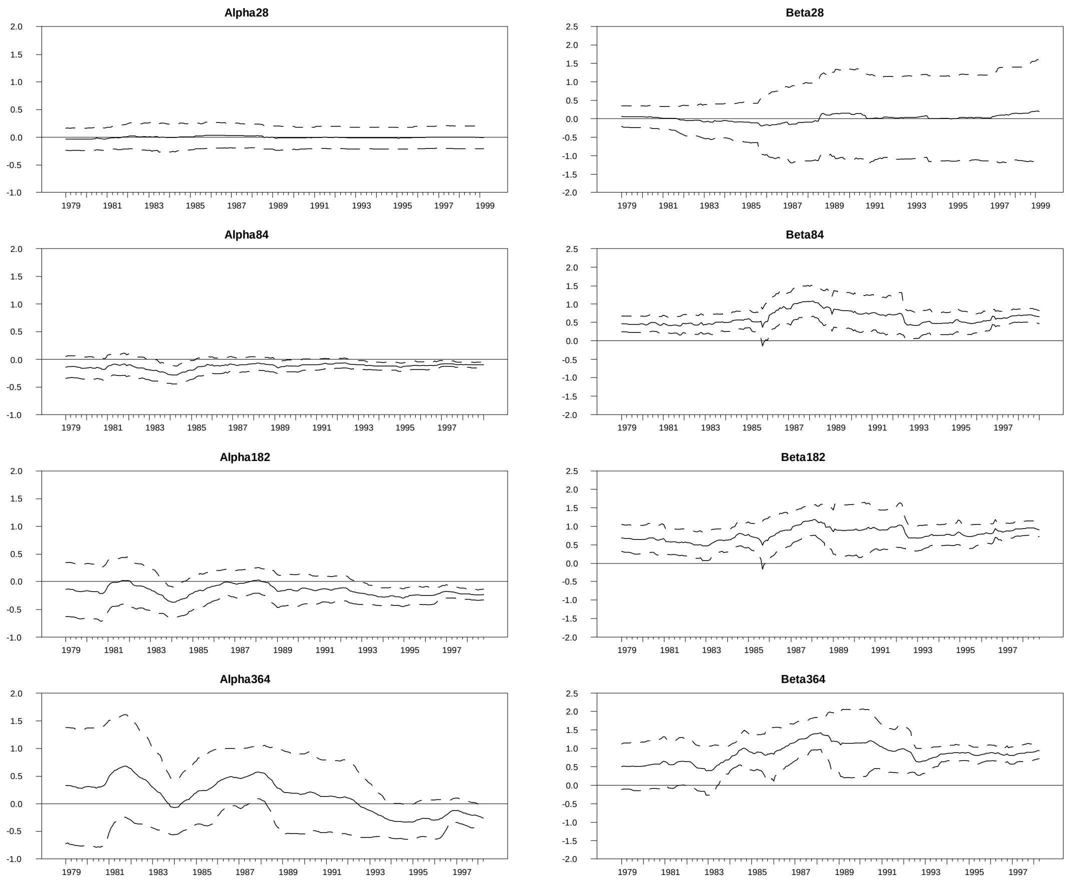


Chart 6: Parameter estimates from rolling regressions of equations (15)-(18) with a window length of four years



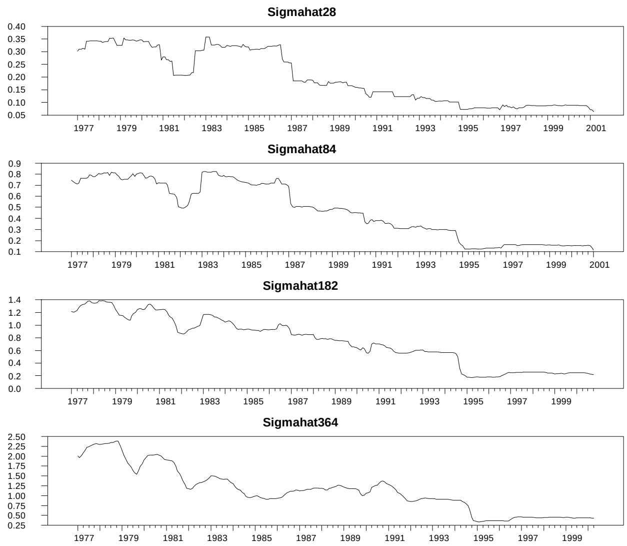
Note: Time index of parameter estimates correspond to the center of the moving window.

Chart 7: Parameter estimates from rolling regressions of equations (15)-(18) with a window length of eight years



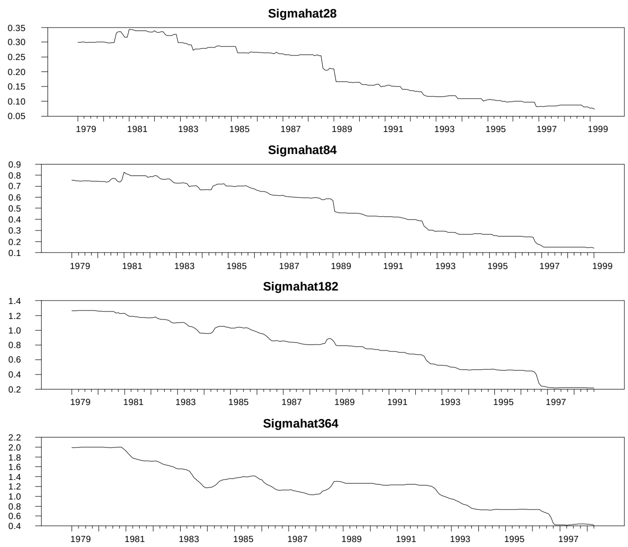
Note: Time index of parameter estimates correspond to the center of the moving window.

Chart 8: Sigmahat from rolling regressions of equations (15)-(18) with a window length of four years



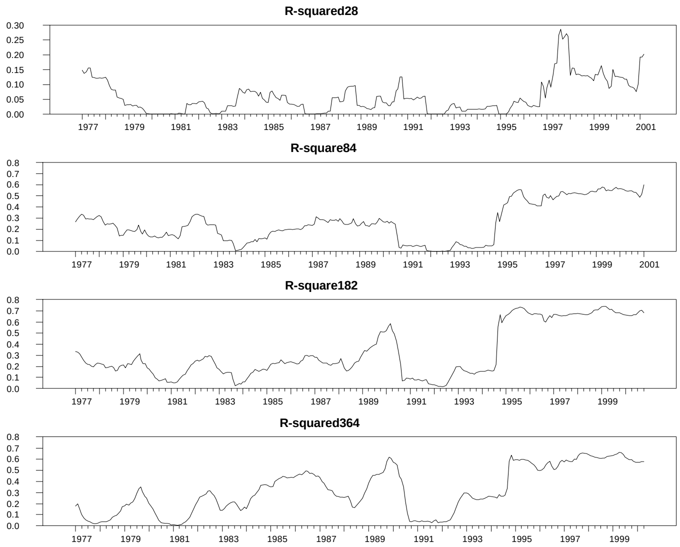
Note: Time index of parameter estimates correspond to the center of the moving window.

Chart 9: Sigmahat from rolling regressions of equations (15)-(18) with window length of eight years



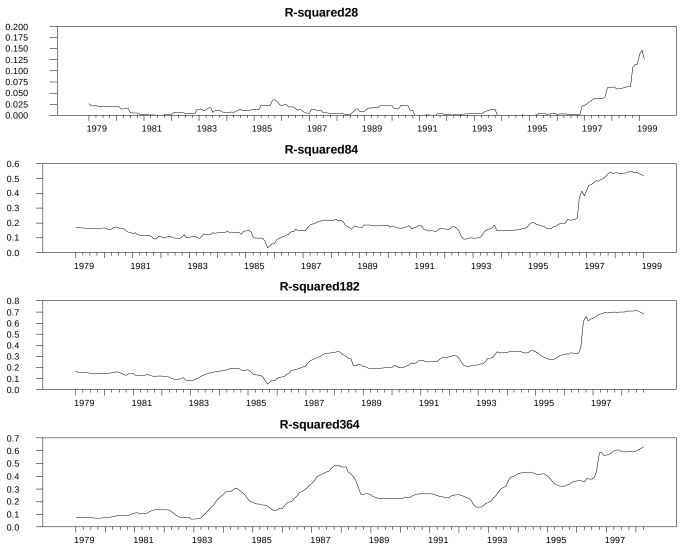
Note: Time index of parameter estimates correspond to the center of the moving window.

Chart 10: R-squared from rolling regression of equations (15)-(18) with window length of four years



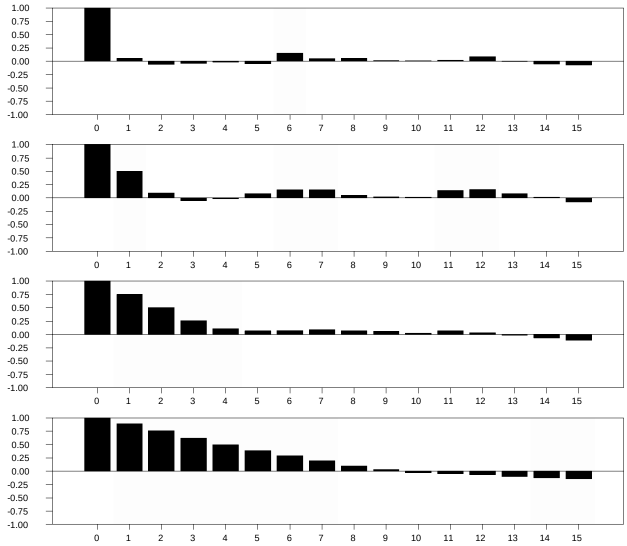
Note: Time index of R^2s correspond to the center of the moving window.

Chart 11: R-squared from rolling regression of equations (15)-(18) with window length of eight years



Note: Time index of R^2s correspond to the center of the moving window.

Chart 12: Residual autocorrelation in equations (15) - (18)



Note: Autocorrelations significantly different from zero (using asymptotic standard errors) at a 5 % significance level are shaded.

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