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Eric Schaling – Sylvester Eijffinger –
Mewael Tesfaselassie
Research Department
17.11.2004

Heterogeneous information
about the term structure, least-
squares learning and optimal
rules for inflation targeting

Suomen Pankin keskustelualoitteita
Finlands Banks diskussionsunderlag

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The views expressed are those of the authors and do not necessarily reflect the views of the Bank of Finland.

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Bank of Finland Discussion Papers 23/2004

Eric Schaling – Sylvester Eijffinger – Mewael Tesfaselassie
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Abstract

In this paper we incorporate the term structure of interest rates into a standard inflation forecast targeting framework. Learning about the transmission process of monetary policy is introduced by having heterogeneous agents – ie central bank and private agents – who have different information sets about the future sequence of short-term interest rates. We analyse inflation forecast targeting in two environments. One in which the central bank has perfect knowledge, in the sense that it understands and observes the process by which private sector interest rate expectations are generated, and one in which the central bank has imperfect knowledge. In the case of imperfect knowledge, the central bank has to learn about private sector interest rate expectations, as the latter affect the impact of monetary policy through the expectations theory of the term structure of interest rates. Here, following Evans and Honkapohja (2001), the learning scheme we investigate is that of least-squares learning (recursive OLS) using the Kalman filter. We find that optimal monetary policy under learning is a policy that separates estimation and control. Therefore, this model suggests that the practical relevance of the breakdown of the separation principle and the need for experimentation in policy may be limited.

Key words: learning, rational expectations, separation principle, Kalman filter, term structure of interest rates

JEL classification numbers: C53, E43, E52, F33

Heterogeeninen tieto korkojen aikarakenteesta, PNS-oppiminen ja optimaaliset inflaatiotavoitteet

Suomen Pankin keskustelualoitteita 23/2004

Eric Schaling – Sylvester Eijffinger – Mewael Tesfaselassie
Tutkimusosasto

Tiivistelmä

Tässä tutkimuksessa sisällytetään korkojen aikarakenne tavalliseen inflaatiotavoitekehikkoon. Rahapolitiikan välittymismekanismia koskeva oppiminen on otettu mukaan siten, että keskuspankilla ja yksityisillä taloudenpitäjillä on eri informaatio korkojen tulevasta aikaurasta. Inflaatioennusteiden kontrollointiin perustuvaa rahapolitiikkaa analysoidaan kahdessa tilanteessa. Niistä ensimmäisessä keskuspankilla on täydellinen tietämys siinä mielessä, että se tuntee yksityisen sektorin inflaatio-odotusten muodostumisprosessin. Toisessa taas tietämys keskuspankin odotusten muodostumisesta on epätäydellistä. Epätäydellisen tietämyksen tapauksessa keskuspankin on opittava yksityisen sektorin korko-odotukset, koska niillä on vaikutusta rahapolitiikan välittymiseen korkorakenteen odotusteorian mukaisesti. Tässä tarkastellaan Evansin ja Honkapohjan (2001) esittämää oppimisprosessia, joka perustuu rekursiivista pienimmän neliösumman menetelmää käyttävään Kalmanin suotimeen. Osoittautuu, että oppimiseen perustuvassa optimaalisessa rahapolitiikassa estimointi- ja kontrolliongelmien ovat erillisiä, toisin kuin on väitetty. Tämän tutkimuksen mallitarkastelu viittaa näin ollen siihen, että separoituvuusperiaatteen väitetyn pettämisen ja siten politiikkakokeiden käytännöllinen merkitys voi olla vähäinen.

Avainsanat: oppiminen, rationaaliset odotukset, separoituvuusperiaate, Kalmanin suodin, korkojen aikarakenne

JEL-luokittelu: C53, E43, E52, F33

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1 Introduction

As pointed out by Bullard (1991), in the three decades since the publication of the seminal work on rational expectations (RE) in the early 1960s, a steely paradigm was forged in the economics profession regarding acceptable modelling procedures. Simply stated, the paradigm was that economic actors do not persist in making foolish mistakes in forecasting over time.

Since the late 1980s researchers have challenged this paradigm by examining the idea that *how* systematic forecast errors are eliminated may have important implications for macroeconomic policy. Researchers who have focused on this question have been studying what is called ‘learning’, because any method of expectations formation is known as a learning mechanism. Thus, since the late 1980s a learning literature, or learning paradigm, developed. An excellent introduction to – and survey of – this paradigm is presented in Evans and Honkapohja (2001).

A different strand of literature in the economics profession has been dealing with optimal control or dynamic optimisation.

In general there are few papers in the literature that combine the themes of *learning* and (optimal) *control*. An exception is recent and important work by Wieland (2000a,b). Wieland (2000a) analyses the situation where a central bank has limited information concerning the transmission channel of monetary policy. Then, the CB is faced with the difficult task of simultaneously *controlling* the policy target and estimating (*learning*) the impact of policy actions. Thus, the so-called separation principle does not hold, and a trade-off between estimation and control arises because policy actions influence estimation (learning) and provide information that may improve future performance. Wieland analyses this trade-off in a simple model with parameter uncertainty and conducts dynamic simulations of the central bank’s decision problem.

In this paper we incorporate the term structure of interest rates in a standard inflation forecast targeting framework. Learning about the transmission process of monetary policy is introduced by having heterogeneous agents – ie the central bank and private agents – who have different information sets about the future sequence of short-term interest rates. We analyse inflation forecast targeting in two environments. One in which the central bank has perfect knowledge, in the sense that it understands and observes the process by which private sector interest rate expectations are generated, and one in which the central bank has imperfect knowledge and has to learn the private sector forecasting rule for short-term interest rates. In the case of imperfect knowledge, the central bank has to learn about private sector interest rate expectations, as the latter affect the impact of monetary policy through the expectations theory of the term structure of interest rates. Here following Evans and Honkapohja (2001), the learning scheme we

investigate is that of least-squares learning (recursive OLS) using the Kalman filter.

We find that optimal monetary policy under learning is a policy that separates estimation and control. Therefore, this model suggests that the practical relevance of the breakdown of the separation principle and the need for experimentation in policy may be limited.

The remainder of this paper is organized as follows. Section 2 and 3 discusses the basic inflation targeting framework and the term structure of interest rates. In Section 4 we solve for the optimal monetary policy rule under perfect knowledge. Imperfect knowledge and the Kalman filter are introduced in Section 5. We conclude in Section 6. The appendices contain the derivation of results for convergence and the optimal policy rules under perfect knowledge and learning.

2 The environment

Monetary policy is conducted by a central bank that controls a short-term nominal interest rate i_t , and that has an exogenously given inflation target, π^* . The authorities aim to minimize deviations of inflation from its assigned target.¹ Consequently, the central bank will choose a sequence of current and future short-term nominal interest rates to meet the objective

$$\text{Min}_{\{i_\tau\}_{\tau=t}^{\infty}} E_t \sum_{\tau=t}^{\infty} \delta^{\tau-t} \left[\frac{1}{2} (\pi_\tau - \pi^*)^2 \right] \quad (2.1)$$

Here π is the inflation (rate) in year t , π^* is the central bank's inflation target, while the parameter δ (which fulfils $0 < \delta < 1$) denotes the discount factor (ie a measure of the policy horizon). The expectations operator E refers to the policymaker's expectations. This expectation is conditional on the central bank's information set in period t .

As in Rudebusch and Svensson (2002), inflation and output are linked by the following short-term Phillips-curve relationship:²

$$\pi_{t+1} = \pi_t + \alpha_1 z_t - \eta_{t+1} \quad (2.2)$$

¹ The objective function assumes strict inflation targeting. An obvious question is whether the results in the paper would – in broad terms – still go through for flexible inflation targeting (that is in the case of additional objectives like output stabilisation and interest rate smoothing)? Preliminary results (not reported here) indicate that this is indeed the case.

² Rudebusch and Svensson (2002) consider additional lags of inflation.

The variable z represents the (log of the) output gap in period t where potential output has been normalized to zero, finally η is a i.i.d productivity (supply) shock

The output gap is determined by the following dynamic relationship:

$$z_{t+1} = \beta_1 z_t - \beta_2 R_t + d_{t+1} \quad (2.3)$$

where R is the long-term real interest rate and d is an i.i.d. demand shock. Again, this relationship is similar to Rudebusch and Svensson (2002). The differences are that here the output gap depends on the long-term real interest rate rather than the short-term real interest rate, and that they consider an additional lagged z term.

Note that from equation (2.3) it appears as if the setting is completely backward looking. The output gap seems to depend only on lagged variables and not on expectations of future variables as in the micro-founded New Keynesian model. However, this is not the entirely true. In Section 3 below we show that the combination of the IS curve and the term structure implies the presence of forward looking elements in the model that makes our (semi-reduced form) IS curve behave quite a bit like the New Keynesian IS curve as employed by Clarida, Gali and Gertler (1999).

We assume that the short real rate (r_t) and the long real rate (R_t) are related by the following version of the Pure Expectations Hypothesis (PEH)

$$r_t = R_t - D(\hat{E}_t R_{t+1} - R_t) \quad (2.4')$$

The expectations operator \hat{E} refers to the private sector's expectations. Here r_t represents the real yield to maturity on a one-period bond which is traded on the interbank money market. The expectations operator \hat{E} refers to private agents' (possibly subjective) expectations. The LHS denotes the (one-period) real holding period return on a long-term bond. The latter's real yield to maturity (R_t) is the long-term real interest rate. The parameter D is defined such that $D + 1$ is equal to Maccaulay's duration.³

For our purposes it turns out to be convenient to rewrite this equation to express the current long real rate as a convex combination of the current short real rate and the expected long real rate in the next period:

$$R_t = (1 - k)r_t + k\hat{E}_t R_{t+1}; \quad k \equiv \frac{D}{1 + D} \quad (2.4)$$

Note that the long and short real interest rates will be equal if the parameter k is equal to zero. In that case the duration of the long-term bond will be equal to one

³ For more details see Eijffinger, Schaling and Verhagen (2000), hereafter ESV.

and there is no distinction between short and long term interest rates. Note that this equation can be rewritten as

$$R_t = (1 - k) \sum_{\tau=t}^{\infty} k^{\tau-t} \hat{E}_t r_{\tau}.$$

Or alternatively, as

$$R_t = (1 - k)r_t + (1 - k) \sum_{\tau=t+1}^{\infty} k^{\tau-t} \hat{E}_t r_{\tau}.$$

It follows that

$$\hat{E}_t R_{t+1} = \left(\frac{1 - k}{k} \right) \sum_{\tau=t+1}^{\infty} k^{\tau-t} \hat{E}_t r_{\tau} \quad (2.5)$$

Thus, in equation (2.4) the long term real interest rate is a weighted average of the current ex ante real short rate and the expected future sequence of future short real rates over the $t + 1 - \text{infinity}$ horizon.

The current short-term real interest rate will be equal to:

$$r_t = i_t - E_t \pi_{t+1} \quad (2.6)$$

Here i_t is the instrument of the central bank (ie the nominal interest rate on the interbank money market) and $E_t \pi_{t+1}$ represents the expected rate of inflation in period $t + 1$ conditional on the information set in period t .

3 The role of forward looking elements and comparison with the New Keynesian model

Before we proceed to solving the model for an inflation targeting central bank, it is worthwhile pointing out some features of the semi-reduced form implied by equations (2.3) to (2.6). For the moment we abstract from the term structure by setting $k = 0$.

In that case the duration of the long-term bond will be equal to one and there is no distinction between short and long term interest rates. Then, (2.3) collapses to:

$$z_{t+1} = \beta_1 z_t - \beta_2 (i_t - E_t \pi_{t+1}) + d_{t+1}$$

This is in marked contrast to the micro-founded New Keynesian model (NKM). Here we mean the IS curve of Clarida, Gali and Gertler (CGG) (1999), namely:

$$z_t = E_t z_{t+1} - \varphi (i_t - E_t \pi_{t+1}) + g_t$$

As pointed out by CGG this equation is obtained by log-linearizing the consumption Euler equation that arises from the household's optimal saving decision. The resulting expression differs from the traditional IS curve (2.3) – apart from the effect of the term structure – mainly because current output depends on expected future output as well as the (ex ante) short real interest rate. Higher expected future output raises current output: Because individuals prefer to smooth consumption, expectation of higher consumption next period (associated with higher expected output) leads them to want to consume more today, which raises current output demand. The negative effect of the real rate on current output, in turn, reflects intertemporal substitution of consumption. In this respect, the interest elasticity in the IS curve, φ , corresponds to the intertemporal elasticity of substitution. Finally, g_t can be interpreted as a demand shock.

Translated into our notation we get:

$$z_t = E_t z_{t+1} - \beta_2 (i_t - E_t \pi_{t+1}) + d_t \tag{3.1'}$$

So, apart from the term structure the IS curve of the NKM differs in two ways from the Rudebusch–Svensson equation: a) current output depends on expected future output rather than on past output, and b) the parameter β_2 is micro founded,

namely it is no longer a free ad hoc parameter but is equal to the intertemporal elasticity of substitution.⁴

CGG point out that it is possible to iterate their IS equation (in our notation equation (3.1')) forward to yield:

$$z_t = E_t \sum_{i=0}^{\infty} \{-\beta_2 [i_{t+1+i} - \pi_{t+1+i}] + d_{t+1+i}\} \quad (3.1)$$

According to CGG this equation illustrates the degree to which beliefs about the future affect current aggregate activity within the NKM. The output gap depends not only on the current real rate and the demand shock, but also on the expected future paths of these two variables.

At this stage it is interesting to compare the above equation and the implications of the forward looking term structure. To keep things simple, for the moment abstract from the backward looking elements in the IS curve. So, for now we set $\beta_1 = 0$. Then, equation (2.3) collapses to

$$z_{t+1} = -\beta_2 R_t + d_{t+1}$$

Combing this expression with our term structure equation (2.4) we get:

$$z_{t+1} = -\beta_2 (1-k) \sum_{\tau=t}^{\infty} k^{\tau-t} \hat{E}_t r_{\tau} + d_{t+1} \quad (3.2)$$

Let us now compare our result (3.2) with CGG (3.1).

We see that in CGG the current level of activity depends on beliefs about future short real interest rates and demand shocks. In our model – with the term structure switched on so $k > 0$, but no output persistence so $\beta_1 = 0$ – the future level of output depends on beliefs about future short real rates. The reason that the ‘dependent variable’ is future rather than current output is because of the control lag of monetary policy. Policy does not control the present level of output (as in CGG) but next year’s level of output (as in our model and Rudebusch–Svensson).

So, apart from the fact that beliefs about the future do not include the demand shock d , the only difference between our ‘IS curve’⁵ and the New Keynesian IS curve is the one-year control lag of monetary policy. Table 3.1 summarizes.

⁴ There is no real difference with respect to the demand shock as in both specifications the effect of the demand shock on output is contemporaneous ($d_{t+1} \rightarrow z_{t+1}$ versus $d_t \rightarrow z_t$).

⁵ Used here as shorthand for the combination of the IS curve and the term structure equation.

Table 3.1

**Effects of the term structure versus the
New Keynesian IS Curve**

$k > 0, \beta_1 = 0$	Clarida, Gali and Gertler
$z_{t+1} = -\beta_2(1-k) \sum_{\tau=t}^{\infty} k^{\tau-t} \hat{E}_t r_{\tau} + d_{t+1}$	$z_t = E_t \sum_{j=0}^{\infty} \{-\beta_2 [i_{t+j} - \pi_{t+1+j}] + d_{t+j}\}$

So, an interesting result to emerge from this Section is that the presence of the term structure in our model generates forward looking elements that have implications very similar to those implied by the New Keynesian IS curve in the CGG model that does not include a term structure. To recap, in the CGG framework the forward looking IS curve implies that the output gap depends not only on the current real rate and the demand shock, but also on the expected future paths of these two variables. In turn, using the combination of a traditional IS curve plus an explicit term structure equation generates a similar result – provided that the degree of inertia in the IS curve is low.

Let's now look at the general case, where there are forward looking elements in the model (so $k > 0$), and where now the inertia in the IS curve is also allowed to play a role (so $\beta_1 > 0$).

First, note that our IS curve (2.3) – using the lag operator L – can be rewritten as

$$z_t = \beta_1 L z_t - \beta_2 R_{t-1} + d_t \Leftrightarrow z_t = \frac{-\beta_2 R_{t-1} + d_t}{1 - \beta_1 L}$$

Thus, the current level of output can be written as⁶

$$z_t = \sum_{j=0}^{\infty} (\beta_1 L)^j \{-\beta_2 R_{t-1} + d_t\}$$

So, the output gap depends not only on the lagged long real interest rate and the current demand shock, but also on the entire past path of these two variables.

Combining this result with the term structure (2.4) we get:

⁶ We have used that

$$\begin{aligned} \frac{-\beta_2 R_{t-1} + d_t}{1 - \beta_1 L} &= (-\beta_2 R_{t-1} + d_t) + \beta_1 (-\beta_2 R_{t-2} + d_{t-1}) + (\beta_1)^2 (-\beta_2 R_{t-3} + d_{t-2}) + \dots \\ &+ (\beta_1)^j (-\beta_2 R_{t-1-j} + d_{t-j}) \end{aligned}$$

$$z_t = \sum_{j=0}^{\infty} (\beta_1 L)^j \{-\beta_2 L(1-k) \sum_{\tau=T}^{\infty} k^{\tau-t} \hat{E}_t r_{\tau} + d_t\} \quad (3.3)$$

Let's now contrast the general result (3.3) (ie the case where $k > 0$ and $\beta_1 > 0$) with CGG (3.1).

We see that in CGG the current level of activity depends on beliefs about future short real interest rates and demand shocks. In our model – with the term structure present so $k > 0$, and with non-zero output persistence so $\beta_1 > 0$ – the present level of output depends on the entire past history of long real rates and demand shocks. However, since the long real rate is equal to the expected sequence of future short rates we have a complex interplay of forward looking and backward looking elements.

So, with the term structure switched on the contrast between our ‘IS curve’ and the New Keynesian IS curve is less stark: like CGG in our model beliefs about future interest rates do affect current economic activity. However, unlike CGG here these beliefs only affect the current level of output through various lags. Table 3.2 summarizes.

Table 3.2 **The ‘IS curve’ versus the New Keynesian IS curve**

$k > 0, \beta_1 > 0$	Clarida, Gali and Gertler
$z_t = \sum_{j=0}^{\infty} (\beta_1 L)^j \{-\beta_2 L(1-k) \sum_{\tau=t}^{\infty} k^{\tau-t} \hat{E}_t r_{\tau} + d_t\}$	$z_t = E_t \sum_{j=0}^{\infty} \{-\beta_2 [i_{t+j} - \pi_{t+1+j}] + d_{t+j}\}$

4 Implementing inflation targeting under perfect knowledge

To get some straightforward results, we assume that the central bank understands and observes the process by which private sector inflation expectations are generated. This is the benchmark case of *perfect knowledge*. We model least-squares learning by the central bank in section 5.

4.1 Timing of events

The timing is that first the private sector (PS) sets its expectation about the sequence of future short real rates – that is, it chooses $\hat{E}_t R_{t+1}$ – and the central bank (CB) then chooses r_t (through the choice of i_t , given $\hat{E}_t \pi_{t+1} = E_t \pi_{t+1}$). The policymaker's best response, $r_t(\pi_t, z_t, E_t[\hat{E}_t R_{t+1}])$ maximizes the monetary

authority's payoff given $E_t[\hat{E}_t R_{t+1}]$. The model is completed by imposing rational expectations on the policymaker, namely, $E_t[E_t \hat{R}_{t+1}] = \hat{E}_t R_{t+1}$. More specific, in the case of perfect knowledge the CB understands and observes the process by which PS interest rate expectations are generated.⁷ How those expectations are generated remains to be specified. The equilibrium ex ante real interest rate is given by the solution of this equation, and is denoted by $r_t^*(\pi_t, z_t, E_t[\hat{E}_t R_{t+1}])$. To summarize, the above case of discretion can be represented as follows. Then, also at time t the CB sets the interest rate based on strict inflation targeting (SIT) and on its correct observation of PS expectations. Figure 4.1 illustrates.

Table 4.1 **Discretion: timing of events**

Time t	
Stage 1:	Stage 2:
<ul style="list-style-type: none"> PS forecasts sequence of future interest rates, ie sets $\hat{E}_t R_{t+1}$. 	<ul style="list-style-type: none"> CB decides on monetary policy according to strict IFT, ie sets $r_t^*(\pi_t, z_t, \hat{E}_t, R_{t+1})$.

4.2 Optimality

In Appendix 2 we show that the first-order condition of this optimization problem is⁸

$$E_t \pi_{t+2} = \pi^* \quad (4.1)$$

Substituting from the constraints it can easily be established that can be easily established that the closed form solution for the ex ante real interest rate is

$$r_t = \frac{1}{\alpha_1 \beta_2 (1-k)} (\pi_t - \pi^*) + \frac{(1+\beta_1)}{\beta_2 (1-k)} z_t - \frac{k}{(1-k)} \hat{E}_t R_{t+1} \quad (4.2)$$

Note that rule (4.2) can be written in different ways, including forms without $\hat{E}_t R_{t+1}$ as in the REE the forecasts are a function of current endogenous variables. We show this in Section 4.3 below, the relevant form of the rule is then equation (4.8).

⁷ So, the central bank knows how much policy 'is in the pipeline' according to financial markets.

⁸ See Bullard and Schaling (2001) and Schaling (2004) for examples of the method of solving for the optimal policy.

The difference with standard Taylor-type monetary policy rules is that now the CB responds to *three* state variables: inflation, output and the private sector forecast of the long real rate. If $k \rightarrow 0$ there is no term structure, and the policy rule collapses to Svensson's (1997) version of the Taylor rule (hereafter the Svensson–Taylor rule).

An interesting characteristic of this solution is that the central bank's optimal level of short-rates is inversely related to PS expectations about its future short rates (because of the minus sign on the term $E_t R_{t+1}$). For example, if the PS expects rates to go up in the future, as a consequence (*ceteris paribus*; given its inflation target) rates can be lower today (and vice versa). The latter (reverse case), ie the PS expects rates to go down, and as a consequence the CB raises (or talks about raising them) reminds us of the old joke about the Bundesbank: 'The BuBA is just like cream, the more you stir it, the thicker it gets'.⁹ The reason for this is that the central bank's inflation forecast – given other state variables such as the present inflation rate and the present output gap – depends on the present level of the real long term interest rate, R_t . So, an optimal forecast implies an optimal level of this variable. Since the optimal long-term rate (that is consistent with strict IT) is a weighted average of the present ex ante optimal real rate and $\hat{E}_t R_{t+1}$, ie $R_t^* = (1 - k)r_t^* + k\hat{E}_t R_{t+1}$, the higher $\hat{E}_t R_{t+1}$ the lower the optimal ex ante real rate can be. Similarly lower expected interest rates necessitate a tighter policy stance today to compensate.

An important limiting case of equation (4.2) is when $k \rightarrow 0$ and there is no difference between long-term and short-term interest rates. Then the policy rule collapses to

$$r_t = \frac{1}{\alpha_1 \beta_2} (\pi_t - \pi^*) + \frac{(1 + \beta_1)}{\beta_2} z_t \quad (4.3)$$

which – as in Svensson (1997, p. 1119) – is essentially a version of the simple policy rule popularized by Taylor (1993).¹⁰ This result will be referred to as the 'Svensson–Taylor' rule.

4.3 The rational expectations solution

It remains to present the rational expectations solution. This is the case where private sector interest rate expectations are formed rationally; ie private agents

⁹ In addition, the Deutsche Bundesbank always considered the long-term interest rate as a reflection of the credibility of its monetary policy.

¹⁰ Taylor rules are often written in terms of nominal interest rates, but given the definition of r_t the rules in equations (4.2) and (4.3) can easily be interpreted in these terms.

think that the CB will implement inflation forecast targeting in each and every period. That is, they think that the CB will set policy according to $E_t \pi_{t+2} = \pi^* \forall t$.

As a first step, solve for the long-term real interest rate. Substituting (4.2) into equation (2.4) we obtain

$$R_t = \frac{1}{\alpha_1 \beta_2} (\pi_t - \pi^*) + \frac{(1 + \beta_1)}{\beta_2} z_t \quad (4.4)$$

The solution for the output gap and inflation under strict IT is

$$z_{t+1} = -z_t - \frac{1}{\alpha_1} (\pi_t - \pi^*) + d_{t+1} \quad (4.5)$$

Leading equation (4.4) by one period and substituting from equations (2.2) and (4.5) we get

$$R_{t+1} = -\frac{\beta_1}{\alpha_1 \beta_2} (\pi_t - \pi^*) - \frac{\beta_1}{\beta_2} z_t + u_{t+1} \quad (4.6)$$

where $u_{t+1} = \frac{(1 + \beta_1)}{\beta_2} d_{t+1} - \frac{1}{\alpha_1 \beta_2} \eta_{t+1}$ is a composite white noise shock, ie a linear combination of the demand and supply shocks (both white noise). Rearranging and taking PS expectations at time t gives

$$\hat{E}_t R_{t+1} = -\frac{\beta_1}{\alpha_1 \beta_2} (\pi_t - \pi^*) - \frac{\beta_1}{\beta_2} z_t \quad (4.7)$$

This is now the solution for the rational expectation of next period's long real rate from the perspective of the private sector. Note that the benchmark case of the model, that of perfect knowledge, relates to the situation where both the policymaker, and the private sector have rational expectations. More specific, in the case of perfect knowledge the CB understands and observes the process by which PS interest rate expectations are generated. In turn those expectations are consistent with the solution for the long-term real interest rate implied by strict IT.

Plugging expression (4.7) into the CB's optimal policy rule (4.2) yields

$$r_t = \frac{(1 + k\beta_1)}{\alpha_1 \beta_2 (1 - k)} (\pi_t - \pi^*) + \frac{(1 + k\beta_1) + \beta_1}{\beta_2 (1 - k)} z_t \quad (4.8)$$

This equation is the equivalent of equation (3.6) of Eijffinger, Schaling and Verhagen (2000) (ESV).¹¹ However, the equations are not strictly comparable because the optimal real interest rate in ESV is in ex post terms, whereas in (4.8) it is in ex ante terms.

4.4 Comparing the rules

It is interesting to compare the optimal rule (4.8) with the Svensson-Taylor rule (4.3).

Comparing the coefficients for inflation and output gap respectively, we see that when the term structure is relevant, ie, $0 < k < 1$,

$$\frac{1 + k\beta_1}{\alpha_1\beta_2(1-k)} > \frac{1}{\alpha_1\beta_2}; \quad \frac{1 + \beta_1 + k\beta_1}{\beta_2(1-k)} > \frac{1 + \beta_1}{\beta_2}$$

That means the primary feature of the optimal rule is that the interest rate appears to be more volatile than according to the Svensson–Taylor rule. The intuition behind this result is as follows.

From equation (4.8) we see that the optimal response of the short-term interest rate to its determinants becomes stronger if the duration of the long bond (D) increases – that is the parameter k becomes larger. This result is driven by a decrease in policy leverage over the long real rate, since the latter will now to a greater extent be determined by *expected future* short real rates at the expense of the *present* short real rate. However, provided central bank preferences are constant over time, a change in duration will not alter the central bank’s optimal intermediate target as expressed in equation (4.1). Therefore, the central bank will have to manipulate its instrument more aggressively, in order to attain the same desired effect on the long-term real interest rate.

¹¹ However, the equations are not completely identical because the optimal real interest rate in ESV is in ex post terms, whereas in (4.8) it is in ex ante terms.

5 Implementing inflation targeting under learning

The case of perfect knowledge can be represented as follows. First, at time t the central bank sets its expectation (forecast) for private sector interest rate expectations. Next, also at time t the private sector sets its forecast, $\hat{E}_t R_{t+1} = x_{t+1}$, of the long term real interest rate for period $t+1$. Then, the CB sets the interest rate at time t based on its own forecast of the long-term real interest rate, where – importantly – the forecast turns out to be correct.

The main problem in practice for a central bank is that private sector agents – financial analysts, investment bankers, institutional investors, etc – have become more and more sophisticated in analyzing and predicting future monetary policy actions of the central bank. This increased degree of sophistication of private sector agents makes it harder for the central bank to understand private sector expectations. Hence, the idea that the CB can forecast or – what is actually equivalent – observe $x_{t+1} = \hat{E}_t R_{t+1}$ without error is hardly realistic.¹² This assumption will now be relaxed.

5.1 The Kalman filter

Suppose the CB can no longer forecast private agents' interest rate expectations x_{t+1} without error. Assume that the CB has a forecast $E_t y_{t+1}$ at time t of x_{t+1} which it subsequently uses to set the short-term interest rate t_t at time t .

More specifically, let y_t be the CB's noisy signal on x_t

$$y_t = x_t + \varepsilon_t \tag{5.1}$$

where y_t is the central bank's signal of x_t , and ε_t is its measurement error.¹³ The only information available to the CB when it sets policy at time t is its forecast of y which is conditional on past values of y ; ie $E[y_{t+1}|t] = E[y_{t+1}|y_{t+1-n}, n = 1, 2, \dots]$. Even ex post, the CB cannot observe separately the two components of y , x and

¹² Strictly speaking one should make a distinction between seeing the value of expectations vs knowing that forecasts are rational, ie knowing the RE forecast function of the private sector. More generally, one could instead assume that CB sees private expectations but does not know that they are rational.

¹³ Subscript 't' denotes variables that are observed or determined at time t , except for the variables x and y where the subscript t refers to the time period for which the expectation, x , or its noisy observation, y , is held.

ε .¹⁴ We assume the measurement error is normally distributed with mean zero and variance σ_ε^2 . So, the central bank's signal is unbiased, but not without error. An important limiting case of (5.1) is when $\sigma_\varepsilon^2 \rightarrow 0$ and we are back to the previous case of perfect knowledge, ie $y_t = x_t$.

To make the problem more tractable we set $\alpha_1 = 1$ and $\pi^* = 0$. These assumptions have the advantage of reducing the dimension of the state space in the central bank's optimal filtering problem. In this way we avoid what Ljungqvist and Sargent (2000) call the 'curse of dimensionality'.¹⁵

Under the above simplifying assumptions equation (4.7) reduces to

$$x_t = \frac{\beta_1}{\beta_2} w_{t-1} = \gamma w_{t-1} \quad \text{where} \quad \gamma \equiv \beta_1 / \beta_2 \quad \text{and} \quad w_{t-1} \equiv (-\pi_{t-1} - z_{t-1}) \quad (4.7')$$

Note that the situation above can be represented as the case where the CB believes that private sector interest rate expectations follow the stochastic process

$$y_t = \gamma w_{t-1} + \varepsilon_t \quad (5.2)$$

corresponding to the true (actual) law of motion of PS interest rate expectations, but that γ is unknown to it (this can be seen by substituting the expression for private sector interest rate expectations (4.7') into equation (5.1)). Thus, here we assume that the central bank employs a reduced form of the expectations formation process that is correctly specified.¹⁶

So, we assume that equation (5.2) is the *perceived law of motion* (PLM) of the central bank and that the policymaker attempts to estimate γ . Following Evans and Honkapohja (2001), this is our key bounded rationality assumption: we back away from the rational expectations assumption, replacing it with the assumption that, in forecasting private sector inflation expectations, the central bank acts like an econometrician.

The central bank's estimates will be updated over time as more information is collected. Letting c_{t-1} denote its estimate through time $t-1$, the central bank's one-step-ahead forecast at $t-1$, is given by

¹⁴ A real world counterpart of our signal processing can be that CBs may get data on PS interest rate expectations (say interest rate futures), which is then taken as a signal of the true PS expectation. Here we focus on one learner: the CB (whose rationality is thus bounded), and let's assume the PS has rational expectations (rationality not bounded). In future we may want to look at two-sided learning where both the PS and the CB are learning.

¹⁵ For the technical details see Appendix D of Schaling (2003).

¹⁶ Instead – as pointed out by Orphanides and Williams (2002) – the learner may be uncertain of the correct form and estimate a more general specification, for example, in our case a linear regression with additional lags of expected inflation which nests (5.2).

$$E_{t-1}[y_t] = c_{t-1} w_{t-1} \quad (5.3)$$

Under this assumption we have the following model of the evolution of the economy. Let Ω_t be the central bank's information set for time t . Suppose that at time $t-1$ the central bank has data on the economy from periods $\tau = t-1, \dots, t-n$. Thus the time $t-1$ information set is $\Omega_{t-1} = \{y_\tau, w_\tau\}_{\tau=t-n}^{t-1}$. Imagine that we have already calculated the ordinary least squares estimate c_{t-1} of γ in the model $(y_{t-1}; w_{t-2}\gamma, \sigma_\varepsilon^2)$. Given the new information, which is provided by the observations y_t, w_{t-1} , we wish to form a revised or updated estimate of γ . Here c_t is the CB's OLS estimate of γ in the model $(y_t; w_{t-1}\gamma, \sigma_\varepsilon^2)$.

The timing of events is summarized in Table 5.1 below.

Table 5.1 **Imperfect knowledge: timing of events**

Time t		
Stage 1: <ul style="list-style-type: none"> • CB forecasts PS interest rate expectations using c_t and w_t; ie sets $E_t[x_{t+1}] = E_t[y_{t+1}]$. 	Stage 2: <ul style="list-style-type: none"> • 2a) PS forecasts long-term real interest rate, ie sets $x_{t+1} = \gamma w_t$ • 2b) CB decides on monetary policy, ie sets $r_t^*(\pi_t, z_t, E_t[y_{t+1}])$. 	Stage 3: <ul style="list-style-type: none"> • 3a) Nature chooses ε_{t+1}, and $y_{t+1} = x_{t+1} + \varepsilon_{t+1}$ realizes. • 3b) CB observes the signal y_{t+1} and forms a revised estimate c_{t+1}. • Back to stage 1, for time $t = t+1$ etc.

Using data through period t , the least squares regression parameter for equation (5.2) can be written in recursive form (see Appendix D of Schaling (2003) for details)

$$c_t = c_{t-1} + \kappa_t (y_t - w_{t-1} c_{t-1}) \quad (5.4)$$

$$p_t = p_{t-1} - \kappa_t w_{t-1} p_{t-1} \quad (5.5a)$$

$$\kappa_t = p_t w_{t-1} (\sigma_\varepsilon^2)^{-1} \quad (5.5b)$$

The method by which the revised estimate of γ is obtained may be described as a filtering process, which maps the sequence of prediction errors into a sequence of

revisions; and $\kappa_t = p_t w_{t-1} (\sigma_\varepsilon^2)^{-1}$ may be described as the gain of the filter, ie the Kalman gain.

Equations (5.4) and (5.5a) are known as the updating, or smoothing equations. These updating equations represent the *learning channel*, through which the current realizations of inflation and the output gap¹⁷ affects next period's estimate or *beliefs* b_{t+1} , where b is a 1×2 row vector of state variables containing the mean and variance of the estimate, ie $b_t = [c_t \ p_t]'$.

5.2 The case of passive learning

In order to get some analytical results, we now consider the case of *passive learning*. This is the case where the central bank disregards the effect of current policy actions on future estimation and prediction. In this case the policy maker treats control and estimation separately.

The central bank will first choose r_t to minimise the expected loss based on its current parameter estimate (its belief about γ). Then, a white noise shock ε_{t+1} occurs and a new realization y_{t+1} can be observed. Before choosing next period's control r_{t+1} the central bank will proceed by updating its estimate (belief) using the new information (w_t, y_{t+1}).

In case of imperfect knowledge – and a passive learning policy in which the central bank separates estimation and control, see Wieland (2000b, 506–507) – that is a central bank who does not internalize the effect of current policy actions on future beliefs – in stage 2b) of Table 5.1 we have

$$r_t = \frac{1}{\beta_2(1-k)} \pi_t + \frac{(1+\beta_1)}{\beta_2(1-k)} z_t - \frac{k}{(1-k)} E_t[\hat{E}_t R_{t+1}] \quad (5.6)$$

where the central bank's forecast of market expectations of future rates is governed by

$$E_t[\hat{E}_t R_{t+1}] = c_t w_t \quad (5.7)$$

Plugging (5.7) in equation (5.6), we get the solution for the central bank's policy rule under *passive learning*

$$r_t = \frac{1}{\beta_2(1-k)} \pi_t + \frac{(1+\beta_1)}{\beta_2(1-k)} z_t + \frac{k}{(1-k)} c_t (\pi_t + z_t) \quad (5.8)$$

¹⁷ Note that $w_t \equiv (-\pi_t - z_t)$

(For a proof see Appendix 3). Note that now we have *four* state variables in the policy rule: inflation, output, the existing parameter estimate, and nominal GDP.¹⁸ In addition to raising interest rates in response to inflation and output being above target and trend, respectively, the central bank now also responds to the level of ‘nominal GDP’. Note that the GDP term in the interest rate rule does not occur because the level of GDP enters the central bank’s loss function.¹⁹

If ‘nominal GDP’ $\pi_t + z_t$ is above (below) its target level (of zero), the central bank raises (lowers) short-term interest rates. The reason it does this, is that the central bank’s optimal level of short-rates is inversely related to its expectation of the PS expectations about its future rates γw_t , which in turn is inversely related to the level of GDP ($w_t = (-\pi_t - z_t)$).²⁰ Thus, the central bank’s optimal level of short-rates is inversely related to its *expectation* of the PS expectations about its future short rates. For example, if the CB *expects* the PS to expect that rates go up in the future, as a consequence (ceteris paribus) short-term interest rates can be lower today (and vice versa).

We also find that – in so far as ‘nominal GDP’ is concerned – the policy rule now becomes *state-contingent*, as the parameter c is in general unequal to γ , and moves in real time. This means that the central bank’s optimal response to the deviation of ‘nominal GDP’ and its target level also becomes state-contingent. Over time the estimate converges (for a proof, see Appendix 1) to the true parameter and the policy under passive learning converges to optimal monetary policy under perfect knowledge (4.8).²¹

5.3 Optimal monetary policy under learning

We now examine how the nature of optimal monetary policy is affected by learning considerations. Under imperfect knowledge the central bank chooses $\{r_t\}_{t=t}^{\infty}$ so as to maximize

¹⁸ Or three state variables, if we split-up nominal GDP in inflation and output. In fact strictly speaking the level of nominal GDP does not enter the rule as we have the sum of the level of output and the inflation rate, rather than the price level. We would get nominal GDP if we normalize the lagged price level p_{t-1} to zero though. In what follows we therefore use ‘nominal GDP’ as shorthand for the sum of the output gap and the inflation rate.

¹⁹ For a recent paper where the central bank targets nominal income *growth*, see Mitra (2003).

²⁰ The occurrence of the third GDP term in the policy rule is not, however, a general result. It depends on the specific simplifying assumptions made about the slope of the Phillips curve and the level of the inflation target.

²¹ With $\alpha_1 = 1$, $\pi^* = 0$, and $E_t \hat{R}_{t+1} = \gamma w_t = -\gamma(\pi_t + z_t)$, where $\gamma = \beta_1 \beta_2^{-1}$

$$E_t \left[\sum_{\tau=t}^{\infty} -\frac{\delta^{\tau-t}}{2} \pi_{\tau}^2 \right] \quad (\text{A2.1}')$$

subject to (2.2) and

$$z_{t+1} = (\beta_1 + \beta_2 k c_t) z_t - \beta_2 (1-k) r_t + \beta_2 k c_t \pi_t + d'_{t+1} \quad (\text{A3.3})$$

$$y_{t+1} = \theta_t \quad (\text{A4.2})$$

$$c_{t+1} = (1 + \varpi_t (\pi_t + z_t)) c_t + \varpi_t \theta_t \quad (\text{A4.3})$$

$$\kappa_{t+1} = \varpi_t \quad (\text{A4.4})$$

$$\kappa_{t+1} = -\psi_t (\pi_t + z_t) (\sigma_{\varepsilon}^2)^{-1} \quad (\text{A4.5})$$

$$p_{t+1} = (1 + \omega_t (\pi_t + z_t)) p_t \quad (\text{A4.6})$$

$$p_{t+1} = \Psi_t \quad (\text{A4.7})$$

Note that nonlinearities enter the problem in five places. First, the output equation becomes nonlinear. This can be seen from the presence of the ‘product terms’ $c_t z_t$ and $c_t \pi_t$ on the right-hand side of (A3.3). There is a third nonlinearity, as the product terms $c_t z_t$ and $c_t \pi_t$ on the right-hand side of the updating equation (A4.3) are multiplied by the Kalman gain $\kappa_{t+1} = \varpi_t$. Since the prediction variance also moves over time, we have two more nonlinearities. First, the Kalman gain in equation (A4.5) depends on the *products* of the prediction variance $p_{t+1} = \psi_t$ and the inflation and output realizations π_t and z_t . Second, the prediction variance itself is governed by the nonlinear first-order difference equation (A4.6).

In Appendix 4 we show that the first-order condition can be expressed as

$$E_t \pi_{t+2} = 0 \quad (\text{A3.6})$$

which is identical to the FOC for the cases of *passive learning* (see Appendix 3) and perfect knowledge (see Appendix 2). This means that the optimal policy is identical to the passive policy. Put differently, estimation and control can be separated and the so-called separation principle holds. Therefore, we can now study the optimal rule under imperfect knowledge in terms of equation (5.8).

5.4 Comparing optimal policy under perfect knowledge and learning

Now we compare the optimal rule under learning with the optimal rule under perfect knowledge. We use standard, illustrative values for α_1 , β_1 and β_2 . We chose the shocks η and d from a normal distribution with mean zero and variance $\sigma_\eta^2 = \sigma_d^2 = 0.078$. Table 5.2 summarizes the parameter values.

Table 5.2 **Parameter Configuration¹**

Parameter	Controls	Value
α_1	Response of inflation to the output gap	1
β_1	Output persistence	0.7
β_2	Elasticity of the output gap with respect to the long-term real interest rate	1
k	Duration of the long bond	0.5
σ_d^2	Variance of the shock to the output gap	0.078
σ_η^2	Variance of the supply shock	0.078
π^*	Policymaker's inflation target	0
σ_ε^2	Variance of the measurement error	1
p_0	Initial value of the prediction variance	3
c_0	Initial value of the parameter estimate	0.75
γ	True value of the parameter	0.7

¹We illustrate our analytical findings using these calibrations.

In Figures 5.1 and 5.2 we display the first 100 of 10,000 observations on the short-term ex ante real interest rate for both the optimal rule under perfect knowledge and the optimal rule under learning. We use 100 observations to keep the Figure relatively clear. Both systems are calculated based on the same realized sequence of shocks. As can be seen from Table 5.3, the primary feature of the optimal rule under learning is that the interest rate exhibits less persistence than the interest rate under perfect knowledge. This feature reflects the phenomenon that the latter rule is linear in state with constant parameters, whereas the optimal rule under learning is state-contingent, ie has time-dependent coefficients that move with the updating of the parameter estimate.

Figure 5.1

Short-term interest rate – optimal rule under perfect knowledge

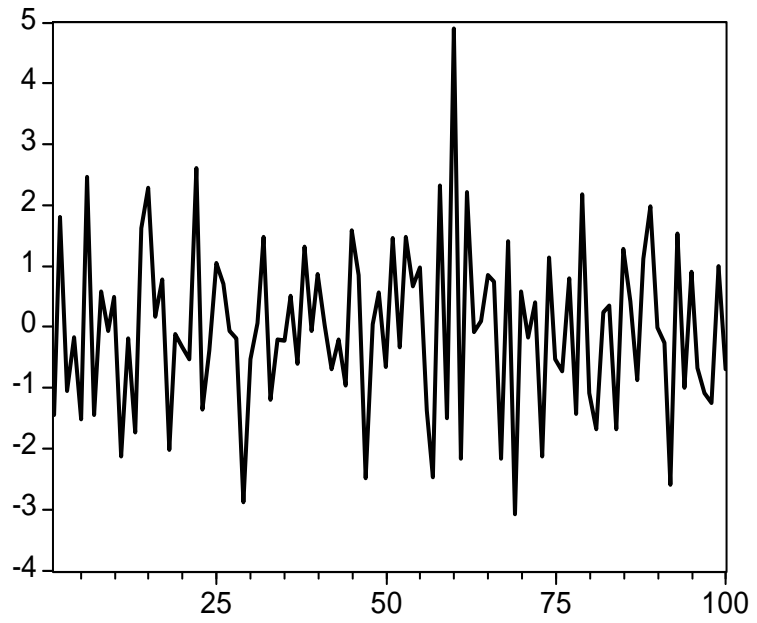


Figure 5.2

Short-term interest rate – optimal rule under learning

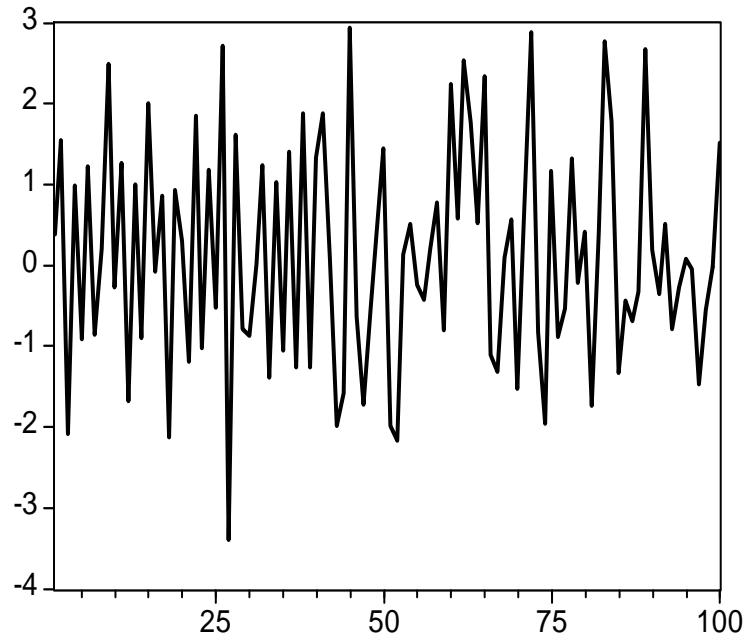


Figure 5.3

Optimal learning – convergence of the parameter estimate to the true value 0.7

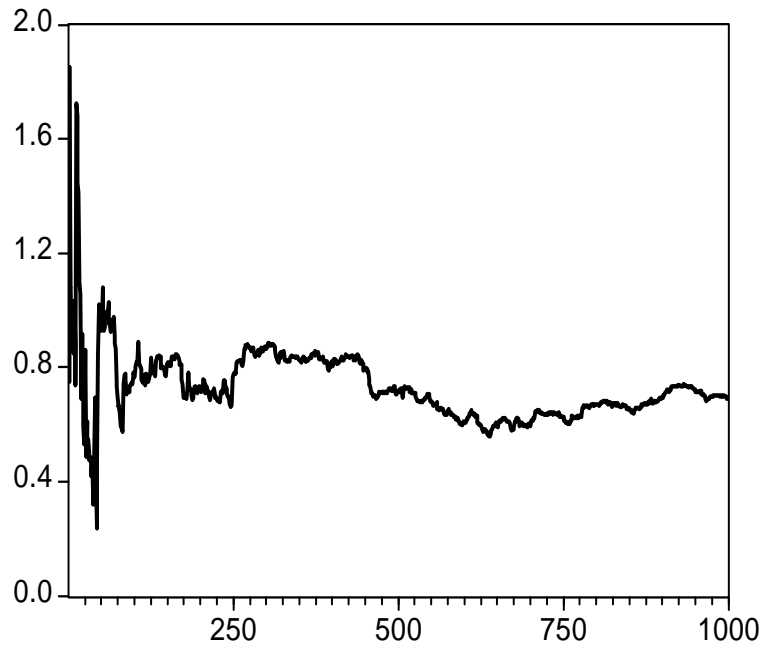


Figure 5.4

Optimal learning – prediction variance of the parameter estimate

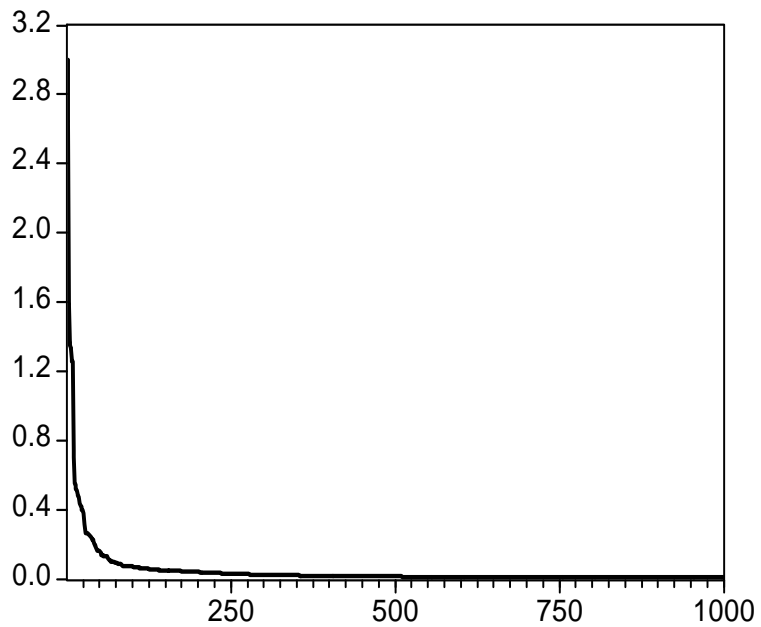


Table 5.3

Summary statistics of first 100 observations

Case	Rule under perfect knowledge	rule under learning
Mean	-0.03579	0.12795
Variance	1.94518	1.89131
Coefficient for AR(1) term	-0.3988	-0.2666

Due to convergence to the true parameter in the learning case, the two rules are almost identical in the last 100 observations. Therefore those observations are not shown. We illustrate convergence with Figures 5.3 and 5.4.

6 Evaluation and concluding remarks

In this Section we put our main result – that the optimal policy under learning coincides with the passive policy, ie that the optimal policy can separate estimation and control – in the context of the dual control literature. We informally discuss how a trade-off between estimation and control might resurface in our model, but find the argument unconvincing.

It is interesting to observe that our one-period objective function differs from Wieland (2000b, p. 506). Using the notation of this paper, Wieland considers

$$L(y_t, r_t) = (y_t - y_t^*)^2 + \lambda(r_t - r_t^*)^2 \quad (6.1)$$

(where he sets $r_t^* = 0$). Thus, in his set-up both the control r_t and the signal y_t affect the agent's pay-off. A similar objective function is used by Beck and Wieland (2002) and Kiefer and Nyarko (1989). Apparently, the loss function (6.1) is standard in the dual control literature.

In the literature on learning and control, the stochastic process to be controlled is usually static in nature. Using the notation of this paper

$$y_t = \alpha + \beta r_t + \varepsilon_t \quad (6.2)$$

where y_t is the target variable and r_t is the control variable.²² Under perfect knowledge of α and β , r_t will be a function of these parameters and as such will be constant. With this type of constraint the optimal value of the control variable under passive learning is a function of the estimates of parameters (certainty-

²² An example is Wieland (2000a,b) who studies the problem of a single decision maker, who attempts to control a linear stochastic process with two unknown parameters, just like (6.2).

equivalence rule) or a function of the parameter estimates and their variances and covariances (myopic rule). Kiefer and Nyarko (1989) show that beliefs and actions r_t converge in the limit. However, the risk is that if r_t converges too quickly, then beliefs may also converge to incorrect values. The need for policy experimentation is therefore relevant here.

The story is different if the process to be controlled is dynamic and the RHS includes the lagged dependent variable, say

$$y_t = \alpha + \beta r_t + \delta y_{t-1} + \varepsilon_t \quad (6.3)$$

In this case, under learning the optimal value of r_t will be a function of the parameter estimates and y_{t-1} . In essence at any point in time, r_t will be reacting to past shocks hitting y_{t-1} and thus actions r_t will never converge (or settle down). The upshot is that as long as the policy maker chooses to react to the state variable y_{t-1} , the control variable r_t will also be stochastic. Kiefer and Nyarko (1989) have shown that beliefs would converge with probability 1 to the truth if actions r_t do not converge. This finding implies that with the RHS variables (r_t and y_{t-1}) showing variations, beliefs will converge with probability 1 to the truth.

In our paper, instead of (6.2) and (6.3) we have

$$y_t = \gamma w_{t-1} + \varepsilon_t \quad (5.2)$$

Thus, it appears that we also need to control a dynamic process. However, our one-period objective function differs markedly from the standard objective function of the dual control literature (6.1).

Note that intuitively strict inflation targeting in our model can be re-interpreted in terms of the dual control literature. For, strict inflation targeting can be thought of as the case where the CB is only interested in minimizing

$$L(y_t, r_t) = (r_t - r_t^*)^2 \quad (6.4)$$

that is, in stabilizing the interest rate at its – time-dependent – target level, where the target level is given by

$$r_t^* = \frac{1}{\beta_2(1-k)} \pi_t + \frac{(1+\beta_1)}{\beta_2(1-k)} z_t + \frac{k}{(1-k)} c_t (\pi_t + z_t) \quad (5.8)$$

Of course, this is simply the case where the central bank – in implementing inflation targeting under imperfect knowledge of the term structure of interest rates – follows its optimal monetary policy rule under learning (with coincides with the passive policy). Thus, the main difference with the standard literature on

learning and control is that in our case the regression to be estimated is different from the process to be controlled, as y_t does not appear in our utility function.²³

Conversely, if we set $\lambda = 0$ in (6.1) the central bank's objective function coincides with the input-target model that is often used in studies of learning by doing such as Jovanovich and Nyarko (1996) and Foster and Rosenzweig (1995). In this case it is also possible to back out an optimal level of the control r_t , ie a certain monetary policy setting that now does not minimize deviations of inflation from the target, but tries to minimize the deviation between the signal y_t and a certain target level.

Since there is an intuitive correspondence between this target level and the state variable $x_t = E_t \hat{R}_{t+1}$, we can think of this case as the case where the central bank is interested in learning the true value of the level of market expectations per se. Thus, here the CB is not targeting inflation, but is targeting 'knowledge about the markets'.

Then the question is what could be the value of 'experimentation' in our model? The answer is: a higher sample variance of w_t leads to a more precise estimate. That is the central bank can engineer a higher volatility in w_t by 'not stabilizing the shocks too well'. This means that the central bank should deviate from the optimal reaction function (5.8) for the case of strict inflation targeting, rule such that the process for w_t becomes more volatile. Some intuition for this is provided by Figure 6.1.

²³ That is, we have the central bank which is estimating the process of private sector expectation formation with w_t on the RHS of the regression. Since w_t never settles down due to supply and demand shocks, we have central bank beliefs converging with probability 1 to the truth, ie Therefore in our model, the central bank's passive learning policy will lead in the limit to the full information rational expectations solution.

Figure 6.1

Constant interest rate rule – convergence of the parameter estimate to the true value 0.7

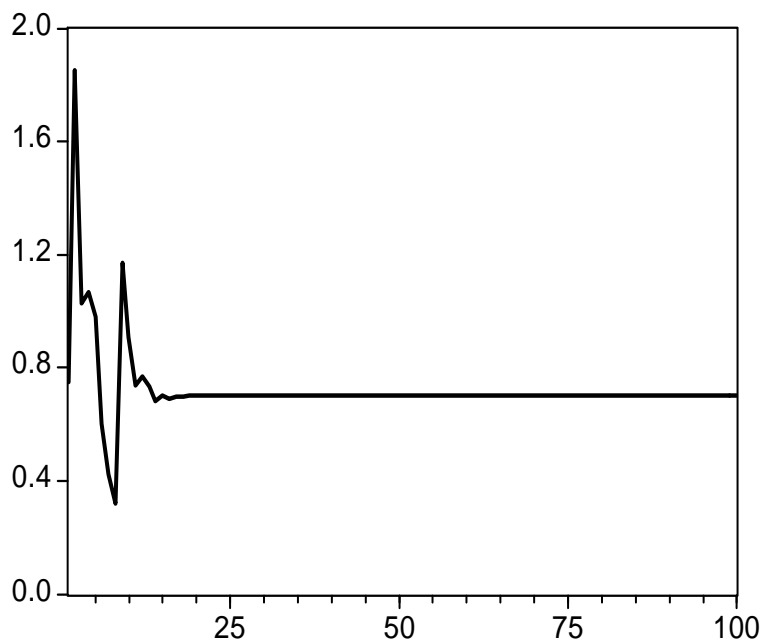


Figure 6.1 displays the first 100 of 10,000 observations on the convergence of the parameter estimate under a constant real interest rate rule, more specifically for the case where the real interest rate stays at its equilibrium or neutral level – which here is normalized at zero. If we compare Figure 6.1 with Figure 5.3 – which illustrates convergence under the optimal interest rate rule – we have an important result. The speed of convergence under a constant interest rate rule is much higher than under the optimal rule!

This suggests that indeed there is a trade-off between learning and control *if the signal enters the utility function*. So, in the case that $(y_t - y^*)$ is an argument in the central bank's loss function – that is if $\lambda \neq 0$ in equation (6.1), we are back in the neighbourhood of the standard dual control literature and the separation principle will break down, indicating that estimation and control cannot be separated.

However, it is hard to see how the objective function (6.1) can be justified. Inflation targeting has become the dominant monetary policy strategy for the major central banks in the world since the late 1990s.²⁴ So, it is clear that the deviation of inflation from its assigned target should be in their objective function.

²⁴ Some central banks – like the Bank of Canada, the Bank of England and the Reserve Bank of Australia – have *explicitly* chosen inflation (forecast) targeting framework as their disciplinary framework. Other central banks – such as the European Central Bank and US Federal Reserve System – have *implicitly* incorporated many elements of inflation targeting in their monetary analysis and policy strategy.

Why, however, would the central bank be interested in limiting the deviation between its noisy observations of market expectations, y_t , and the true values of those expectations? The only clear rationale would be if it needs to know those market expectations as an essential part of the monetary transmission mechanism. This is the avenue we have followed in this paper. However, apart from the need to learn these expectations *for the sake of controlling inflation* there is no reason whatsoever why understanding those expectations in itself should be one of the goals of monetary policy. Therefore, there is no good case for having λ different from 0 and therefore also no good case supporting a trade-off between estimation and control. Therefore, this model suggests that the practical relevance of the breakdown of the separation principle and the need for experimentation in policy may be limited.

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Appendix 1

Convergence of stochastic recursive algorithms

A1.A Sample has been generated by nature

Let

$$R_t = t^{-1} \sum_{i=1}^t (w_{i-1})^2 \quad (\text{A1.1})$$

Then in estimating the model $y_t = \gamma w_{t-1} + \varepsilon_t$, the least squares formula for the parameter estimate c_t can be written in recursive form

$$c_t = c_{t-1} + t^{-1} R_t^{-1} w_{t-1} (y_t - w_{t-1} c_{t-1})$$

or replacing y_t by $\gamma w_{t-1} + \varepsilon_t$,

$$c_t = c_{t-1} + t^{-1} R_t^{-1} w_{t-1} (w_{t-1} (\gamma - c_{t-1}) + \varepsilon_t) \quad (\text{A1.2})$$

(A1.1) can also be written in recursive form

$$R_t = R_{t-1} + t^{-1} (w_{t-1}^2 - R_{t-1}) \quad (\text{A1.3})$$

(the system (1A) and (1C) is the same as Evans and Honkapohja (2001) (hereafter EH) equation (2.9) pp. 33).

To put (A1.2) and (A1.3) in standard form we rather use R_{t-1} instead of R_t on the RHS of this equation. The appropriate way to handle it is to define another variable S such that $S_{t-1} = R_t$ (see EH page 37). The system then becomes

$$c_t = c_{t-1} + t^{-1} S_{t-1}^{-1} w_{t-1} (w_{t-1} (\gamma - c_{t-1}) + \varepsilon_t) \quad (\text{A1.4})$$

$$S_t = S_{t-1} + t^{-1} \left(\frac{t}{t+1} \right) (w_t^2 - S_{t-1}) \quad (\text{A1.5})$$

Next rewrite equation (A1.4) as

$$c_t = c_{t-1} + t^{-1} S_{t-1}^{-1} w_{t-1} [w_{t-1} (T(c_{t-1}) - c_{t-1}) + \varepsilon_t] \quad (\text{A1.4}')$$

where T implicitly defines the mapping from the PLM to the ALM

$$T(c_{t-1}) = \gamma \quad (\text{A1.6})$$

The interpretation of the ALM is that it describes the stochastic process followed by the economy if forecasts are made under the fixed rule given by the PLM. Here of course that stochastic process, the ALM, is the data generating process (DGP) (here the sample is generated by nature) – which is independent of the PLM – and the PLM is the recursive estimate of the ALM (or nature).

The system (A1.4')–(A1.5) is now implicitly in standard form with the following definition of variables:

$$\theta_t = (c_t, S_t)'; \quad X_t = (w_t, w_{t-1}, \varepsilon_t)' \quad \text{and} \quad g_t = t^{-1}$$

So the system (A1.4')–(A1.5) can now be written as

$$\theta_t = \theta_{t-1} + g_t Q(t, \theta_{t-1}, X_t) \quad (\text{A1.7})$$

In the case above the state vector X_t follows an exogenous stochastic process; ie the sample has been generated by nature. However, as pointed out by EH, p. 35 this is not at all essential. In particular, in the general framework, X_t can be permitted to follow a VAR (vector autoregression) with parameters that depend on $\theta_{t-1} = (c_{t-1}, S_{t-1})'$. Evans and Honkapohja (2001) state that this issue is discussed fully in Chapters 6 and 7 of their book, and is relevant for the cases of passive and optimal learning.

The function Q expresses the way in which the estimate θ_{t-1} (or rather a vector of parameter estimates or *beliefs*) is revised in line with last period's observations. Here, θ_{t-1} will include all components of c_{t-1} and S_{t-1} , R_t , X_t is the state vector that includes the effects of w_t , w_{t-1} and ε_t , and g_t is a deterministic sequence of 'gains' – ie a non-increasing sequence of positive numbers – satisfying $\lim_{t \rightarrow \infty} t g_t = 1$. We are interested in the conditions under which $\lim_{t \rightarrow \infty} \theta_t = \bar{\theta}$, where $\bar{\theta}$ solves either $EQ(X_t, \bar{\theta}) = 0$ in the case that $\{X_t\}$ is drawn from a distribution that is stationary or $\lim_{t \rightarrow \infty} EQ(X_t, \bar{\theta}) = 0$ in the case that $\{X_t\}$ is asymptotically stationary (for the latter case see Appendix A1.B)).

As pointed out by Sargent (1993, 39–41), it has been discovered that the limiting behavior of a sequence $\{\theta_t\}$ determined by stochastic difference equation (A1.7) is described by an associated differential equation,

$$\frac{d\theta}{d\tau} = EQ(X, \theta_\tau) \quad (\text{A1.8})$$

where $EQ(X,\theta)$ is the expected value of $Q(X,\theta)$, evaluated with respect to the asymptotic stationary distribution of $\{X_t\}$ and τ denotes ‘notional’ or ‘artificial’ time (see EH pp. 31).

Having shown that the system can be placed in standard SRA (stochastic recursive algorithm) form, the next step is to compute the associated ODE. Therefore, we have to compute $EQ(X,\theta)$.

The easiest way to do this is to look at the two components of Q separately. The first component of Q , giving the revisions to c_{t-1} is given by

$$Q_c(t, \theta_{t-1}, X_t) = S_{t-1}^{-1} w_{t-1} [w_{t-1} (T(c_{t-1}) - c_{t-1}) + \varepsilon_t] \quad (A1.9)$$

Hence, fixing the value of c and S , and computing the expectation over X_t we get

$$\begin{aligned} h_c(c, S) &= \lim_{t \rightarrow \infty} EQ_c(t, \theta_{t-1}, X_t) \\ &= \lim_{t \rightarrow \infty} ES^{-1} w_{t-1} [w_{t-1} (T(c) - c) + \varepsilon_t] \\ &= \lim_{t \rightarrow \infty} ES^{-1} [w_{t-1}^2 (T(c) - c) + w_{t-1} \varepsilon_t] \end{aligned} \quad (A1.10)$$

Similarly, the second component of Q is given by

$$Q_s(t, \theta_{t-1}, X_t) = \left(\frac{t}{t+1} \right) [w_t^2 - S_{t-1}] \quad (A1.11)$$

Hence fixing the value of c and S and computing the expectation over X_t we get

$$h_s(c, S) = \lim_{t \rightarrow \infty} EQ_s(t, \theta_{t-1}, X_t) = \lim_{t \rightarrow \infty} \left(\frac{t}{t+1} \right) E[w_t^2 - S]$$

Since $Ew_t^2 = Ew_{t-1}^2 = \text{Var}(w_t) = \sigma_w^2$, $Ew_{t-1}\varepsilon_t = 0$, and $\lim_{t \rightarrow \infty} t/(t+1) = 1$ we obtain

$$h_c(c, S) = \frac{\sigma_w^2}{S} (T(c) - c) \quad (A1.12)$$

$$h_s(c, S) = \sigma_w^2 - S \quad (A1.13)$$

where $Ew_t^2 = Ew_{t-1}^2 = \sigma_w^2$ is the unconditional second moment of w_t . In the case where the sample has been generated by nature, to make sure that the (asymptotic) variance $Ew_t^2 = Ew_{t-1}^2 = \sigma_w^2$ exists one can, for example, permit w_t to follow a stationary exogenous AR (autoregressive) process, driven by a white noise shock with bounded moments.

The stochastic approximation approach associates an ordinary differential equation (ODE) with the stochastic recursive algorithm,

$$\frac{d\theta}{d\tau} = \text{EQ}(X, \theta_\tau) = h(\theta(\tau)) \quad (\text{A1.14})$$

We can write the differential equation component by component to obtain

$$\frac{dc}{d\tau} = \text{EQ}(X, c_\tau) = h(c(\tau)) = \frac{\sigma_w^2}{S} (T(c) - c) \quad (\text{A1.12}')$$

$$\frac{dS}{d\tau} = \text{EQ}(X, S_\tau) = h(S(\tau)) = \sigma_w^2 - S \quad (\text{A1.13}')$$

As pointed out by EH, p. 38 this system is recursive (that is we ‘first’ compute the variance of the estimated parameter, or the ‘Kalman gain’ and then proceed in updating the estimate) and the second equation is globally stable²⁵ with $S \rightarrow \sigma_w^2$

from any starting point. It follows that $\frac{\sigma_w^2}{S} \rightarrow 1$ from any starting point, provided

S is different from zero along the path, and hence that the stability of the differential equations (A1.12’) and (A1.13’) is determined entirely by the stability of the smaller dimension non-homogenous equation

$$\frac{dc}{d\tau} = (T(c) - c) = Ac = -c + \gamma \quad (\text{A1.15})$$

where I have used (A1.6).

Clearly $c = \gamma$ is a stationary solution. The general solution [see eg Sargent (1993, p. 41)] is

$$c(t) = \gamma + (c(0) - \gamma)e^{-t}$$

which converges to γ for any initial value $c(0)$.

²⁵ Clearly $S = \sigma_w^2$ is a stationary solution. The general solution [see eg Sargent (1993, p. 41)] is $S(t) = \sigma_w^2 + (S(0) - \sigma_w^2)e^{-t}$ which converges to σ_w^2 for any initial value $S(0)$.

A1.B Convergence under passive learning

In the case where the central bank engages in estimation and control the data generating process for w_t is not exogenous anymore. Rather it follows an AR(1) process where the coefficient on the lagged term is a function of c_t . To see this, first solve for the long-term real interest rate. Substituting (5.8) into equation (2.4) and combining the result with (4.7') we obtain

$$R_t = \frac{1}{\beta_2} \pi_t + \frac{1 + \beta_1}{\beta_2} z_t - k[c_t - \gamma] w_t \quad (\text{A1.16})$$

Then, we need the equilibrium equations for inflation and output gap²⁶:

$$z_{t+1} = -[1 - k(c_t - \gamma)]z_t - [1 - k(c_t - \gamma)]\pi_t + d_{t+1} \quad (\text{A1.17})$$

$$\pi_{t+1} = \pi_t + z_t - \eta_{t+1} \quad (\text{A1.18})$$

Then adding (A1.17) and (A1.18) we get

$$\pi_{t+1} + z_{t+1} = k(c_t - \gamma)(\pi_t + z_t) + d_{t+1} + \eta_{t+1} \quad (\text{A1.19})$$

or, in terms of w_t

$$w_{t+1} = k(c_t - \gamma)w_t - (d_{t+1} + \eta_{t+1}) \quad (\text{A1.20})$$

The difference with the case of an exogenous data sequence is that now we need to make sure that $\lim_{t \rightarrow \infty} E w_t^2$ (which depends on the magnitude of $k(c_t - \gamma)$ in the AR(1) process) exists and is finite. The reason is that since we are interested in *local convergence*, it is necessary that in deriving the ODE, the process (A1.20) be asymptotically stationary. For this we need to have $c_t = c$ sufficiently close to γ (the fixed point of interest) such that $|k(c - \gamma)| < 1$. Then the process

$$w_{t+1} = k(c - \gamma)w_t - (d_{t+1} + \eta_{t+1}) \quad (\text{A1.21})$$

will have a bounded second moment in the limit. Let $\lim_{t \rightarrow \infty} E[w_t(c)]^2 = \text{Var}_w(c)$. Denote the stationary points for c and S by \bar{c} and \bar{S} respectively. The ODE system is

²⁶ The solution for the output gap z can readily be obtained by substituting (A1.16) into (2.3).

$$\frac{dc}{d\tau} = h_c(c, S) = \frac{\text{Var}_w(c)}{S} (T(c) - c) \quad (\text{A1.22})$$

$$\frac{dS}{d\tau} = h_s(c, S) = \text{Var}_w(c) - S \quad (\text{A1.23})$$

Then as in Appendix (A1.A) the stability of the ODE system (A1.22) and (A1.23) depends on the local stability of (A1.22) at $\bar{c} = \gamma$. The general solution in real time will be

$$c(t) = \gamma + (c(0) - \gamma)e^{-t}$$

while the stationary solution will be $c(t) = \gamma$.

Appendix 2

Optimal monetary policy under perfect knowledge

The central bank chooses $\{r_\tau\}_{\tau=t}^\infty$ so as to maximize

$$E_t \left[\sum_{\tau=t}^{\infty} -\frac{\delta^{\tau-t}}{2} (\pi_\tau - \pi^*)^2 \right] \quad (\text{A2.1})$$

subject to

$$\pi_{t+1} = \pi_t + \alpha_1 z_t - \eta_{t+1} \quad (\text{A2.2})$$

$$z_{t+1} = \beta_1 z_t - \beta_2 R_t + d_{t+1} \quad (\text{A2.3})$$

$$R_t = (1-k)r_t + k\hat{E}_t R_{t+1} \quad (\text{A2.4})$$

We can reformulate the problem above as choosing the indirect control variable $\{u_\tau\}_{\tau=t}^\infty$ to maximize

$$E_t \left[\sum_{\tau=t}^{\infty} -\frac{\delta^{\tau-t}}{2} (x_\tau - \pi^*)^2 \right] \quad (\text{A2.5})$$

subject to

$$x_{t+1} = x_t + u_t + \xi_{t+1} \quad (\text{A2.6})$$

where $x_t = E_t \pi_{t+1}$ is the new state variable, $u_t = \alpha_1 E_t z_{t+1}$ is the new control variable and $\xi_{t+1} = -\eta_{t+1} + \alpha_1 d_{t+1}$.²⁷ We solve this problem by the method of Lagrange multipliers.²⁸

The Lagrangian for this problem is

²⁷ Equation (A2.6) is derived by leading (A1.18) by one period and taking expectations as of time $t+1$. This gives $E_{t+1} \pi_{t+2} = \pi_{t+2} + a_1 z_{t+1}$. The RHS variables can be decomposed as follows: $\pi_{t+1} = E_t \pi_{t+1} - \eta_{t+1}$ and $\alpha_1 z_{t+1} = \alpha_1 (E_t z_{t+1} + d_{t+1})$. Then we have $E_{t+1} \pi_{t+2} = E_t \pi_{t+1} + \alpha_1 E_t z_{t+1} - \eta_{t+1} + \alpha_1 d_{t+1}$.

²⁸ For a discussion of the relative merits of the methods of dynamic programming and Lagrange, see Schaling (2001).

$$L = E_t \left[\sum_{\tau=t}^{\infty} \left\{ -\frac{\delta^{\tau-t}}{2} (x_{\tau} - \pi^*)^2 - \delta^{\tau-t+1} \mu_{\tau+1} (x_{\tau+1} - x_{\tau} - u_{\tau} - \xi_{\tau+1}) \right\} \right] \quad (A2.7)$$

The first order conditions are

$$\frac{\partial L}{\partial u_t} = \delta E_t \mu_{t+1} = 0 \quad (A2.8)$$

$$\frac{\partial L}{\partial x_t} = -(x_t - \pi^*) - \mu_t + \delta E_t \mu_{t+1} = 0 \quad (A2.9)$$

From equation (A2.8) we have $E_t \mu_{t+1} = 0$. Using this result in equation (A2.9) gives

$$\mu_t = -(x_t - \pi^*) \quad (A2.10)$$

Leading equation (A2.10) by one period and taking expectations at time t yields

$$E_t \mu_{t+1} = -(E_t x_{t+1} - \pi^*) \quad (A2.11)$$

Since we have defined $x_{t+1} = E_{t+1} \pi_{t+2}$, using (A2.8) and the law of iterated expectations the first order condition can be expressed as

$$E_t \pi_{t+2} = \pi^* \quad (A2.12)$$

Finally we combine (A2.12), (A2.2), (A2.3) and (A2.4) to get equation (4.2) in the main text.

Appendix 3

Passive learning

In the case of passive learning at stage 1 the central bank first forms a sample estimate of the unknown parameter γ , and takes this estimate c_t as given when it subsequently sets policy at stage 2 in the same period. Thus, the setup of the problem is similar to the case of perfect knowledge analyzed in Appendix 2 – but with the additional simplifications that $\pi^* = 0$ and $\alpha_1 = 1$.

The model can now be written as follows. For the output gap, as before we decompose z_{t+1} into the central bank's forecast $E_t z_{t+1}$ and its forecast error. To do this, first take expectations of (A2.3) and (A2.4) at time t

$$E_t z_{t+1} = \beta_1 z_t - \beta_2(1-k)r_t - \beta_2 k E_t [\hat{E}_t R_{t+1}] \quad (\text{A3.1})$$

Combining (A3.1) with equation (5.6) we get

$$\begin{aligned} E_t z_{t+1} &= \beta_1 z_t - \beta_2(1-k)r_t - \beta_2 k c_t w_t \\ &= \beta_1 z_t - \beta_2(1-k)r_t + \beta_2 k c_t \pi_t + \beta_2 k c_t z_t \end{aligned} \quad (\text{A3.1}')$$

The actual process for z_{t+1} is given by

$$z_{t+1} = \beta_1 z_t - \beta_2(1-k)r_t + \beta_2 k \gamma \pi_t + \beta_2 k \gamma z_t + d_{t+1} \quad (\text{A3.2})$$

Subtracting (A3.1') from (A3.2) yields

$$\begin{aligned} z_{t+1} &= (\beta_1 + \beta_2 k c_t) z_t - \beta_2(1-k)r_t + \beta_2 k c_t \pi_t + d'_{t+1} \\ &= E_t z_{t+1} + d'_{t+1} \end{aligned} \quad (\text{A3.3})$$

Note that now the output equation becomes *nonlinear*. This can be seen from the presence of the 'product terms' $c_t z_t$ and $c_t \pi_t$ on the right-hand side of (A3.3).

The term $d'_{t+1} = -\beta_2 k(c_t - \gamma)(\pi_t + z_t) + d_{t+1}$ is the central bank's forecast error with respect to next period's level of the output gap. Compared to the case of perfect knowledge it can be seen that this error now consists of two terms: (i) the additive demand shock d_{t+1} , and (ii) a term that depends on its recursive forecast error of market expectations of next period's long real interest rate $-\beta_2 k(c_t - \gamma)(\pi_t + z_t)$. It is clear that if $c_t \rightarrow \gamma$, $d'_{t+1} \rightarrow d_{t+1}$ and results collapse to those under perfect knowledge (for the case that $\pi^* = 0$ and $\alpha_1 = 1$).

The algebra is now the same as in Appendix 2, except that we have d'_{t+1} instead of d_{t+1} . That is, we can reformulate the problem above as choosing the indirect control variable $\{u_\tau\}_{\tau=t}^\infty$ to maximize

$$E_t \left[\sum_{\tau=t}^{\infty} -\frac{\delta^{\tau-t}}{2} (x_\tau)^2 \right] \quad (\text{A3.4})$$

subject to

$$x_{t+1} = x_t + u_t + \xi'_{t+1} \quad (\text{A3.5})$$

where all variables are defined as before and $\xi'_{t+1} = -\eta_{t+1} + d'_{t+1}$.

Following the same logic as in Appendix 2, the first order condition can be expressed as

$$E_t \pi_{t+2} = 0 \quad (\text{A3.6})$$

Finally we combine (A3.6) with (A2.2) and (A3.1') to get equation (5.8) in the main text.

Appendix 4

Optimal learning with variable gain and variable prediction variance

The central bank chooses $\{r_\tau\}_{\tau=t}^\infty$ so as to maximize (A2.1) subject to (A2.2) and

$$z_{t+1} = (\beta_1 + \beta_2 k c_t) z_t - \beta_2 (1 - k) r_t + \beta_2 k c_t \pi_t + d'_{t+1} \quad (\text{A4.1})$$

$$y_{t+1} = \theta_t \quad (\text{A4.2})$$

$$c_{t+1} = (1 + \varpi_t (\pi_t + z_t)) c_t + \varpi_t \theta_t \quad (\text{A4.3})$$

$$\kappa_{t+1} = \varpi_t \quad (\text{A4.4})$$

$$\kappa_{t+1} = -\psi_t (\pi_t + z_t) (\sigma_\varepsilon^2)^{-1} \quad (\text{A4.5})$$

$$p_{t+1} = (1 + \omega_t (\pi_t + z_t)) p_t \quad (\text{A4.6})$$

$$p_{t+1} = \Psi_t \quad (\text{A4.7})$$

The Lagrangian for this problem is

$$L = E_t \sum_{\tau=t}^{\infty} \left\{ \begin{array}{l} -\frac{\delta^{\tau-t}}{2} \pi_\tau^2 - \delta^{\tau-t+1} \mu_{\tau+1}^1 (\pi_{\tau+1} - \pi_\tau - z_\tau + \eta_{\tau+1}) \\ -\delta^{\tau-t+1} \mu_{\tau+1}^2 (z_{\tau+1} - (\beta_1 + \beta_2 k c_\tau) z_\tau \\ + \beta_2 (1 - k) r_\tau - \beta_2 k c_\tau \pi_\tau - d'_{\tau+1}) \\ -\delta^{\tau-t+1} \mu_{\tau+1}^3 (c_{\tau+1} - [1 + \varpi_\tau (\pi_\tau + z_\tau)] c_\tau - \varpi_\tau \theta_\tau) \\ -\delta^{\tau-t+1} \mu_{\tau+1}^4 (y_{\tau+1} - \theta_\tau) \\ -\delta^{\tau-t+1} \mu_{\tau+1}^5 \left(\kappa_{\tau+1} + \psi_\tau (\pi_\tau + z_\tau) (\sigma_\varepsilon^2)^{-1} \right) \\ -\delta^{\tau-t+1} \mu_{\tau+1}^6 (\kappa_{\tau+1} - \varpi_\tau) \\ -\delta^{\tau-t+1} \mu_{\tau+1}^7 (p_{\tau+1} - (1 + \varpi_\tau (\pi_\tau + z_\tau)) p_\tau) \\ -\delta^{\tau-t+1} \mu_{\tau+1}^8 (p_{\tau+1} - \Psi_\tau) \end{array} \right\} \quad (\text{A4.8})$$

The first order conditions are

$$\frac{\partial L}{\partial r_t} = -\beta_2(1-k)\delta E_t \mu_{t+1}^2 = 0 \quad (\text{A4.9})$$

$$\frac{\partial L}{\partial c_t} = \delta \beta_2 k (\pi_t + z_t) E_t \mu_{t+1}^2 - \mu_t^3 + \delta [1 + \varpi_t (\pi_t + z_t)] E_t \mu_{t+1}^3 = 0 \quad (\text{A4.10})$$

$$\frac{\partial L}{\partial \theta_t} = \delta \varpi_t E_t \mu_{t+1}^3 + \delta E_t \mu_{t+1}^4 = 0 \quad (\text{A4.11})$$

$$\frac{\partial L}{\partial y_t} = -\mu_t^4 = 0 \quad (\text{A4.12})$$

$$\frac{\partial L}{\partial \kappa_t} = -\mu_t^5 - \mu_t^6 = 0 \quad (\text{A4.13})$$

$$\begin{aligned} \frac{\partial L}{\partial \pi_t} &= -\pi_t - \mu_t^1 + \delta E_t \mu_{t+1}^1 + \delta \beta_2 k c_t E_t \mu_{t+1}^2 + \delta \varpi_t c_t E_t \mu_{t+1}^3 \\ &\quad - \delta \psi_t (\sigma_\varepsilon^2)^{-1} E_t \mu_{t+1}^5 + \delta \varpi_t p_t E_t \mu_{t+1}^7 = 0 \end{aligned} \quad (\text{A4.14})$$

$$\begin{aligned} \frac{\partial L}{\partial z_t} &= -\mu_t^2 + \delta E_t \mu_{t+1}^1 + \delta (\beta_1 + \beta_2 k c_t) E_t \mu_{t+1}^2 + \delta \varpi_t c_t E_t \mu_{t+1}^3 \\ &\quad - \delta \psi_t (\sigma_\varepsilon^2)^{-1} E_t \mu_{t+1}^5 + \delta \varpi_t p_t E_t \mu_{t+1}^7 = 0 \end{aligned} \quad (\text{A4.15})$$

$$\frac{\partial L}{\partial \varpi_t} = \delta [c_t (\pi_t + z_t) + \theta_t] E_t \mu_{t+1}^3 + \delta E_t \mu_{t+1}^6 + \delta (\pi_t + z_t) p_t E_t \mu_{t+1}^7 = 0 \quad (\text{A4.16})$$

$$\frac{\partial L}{\partial p_t} = -\mu_t^7 + \delta [1 + \varpi_t (\pi_t + z_t)] E_t \mu_{t+1}^7 - \mu_t^8 = 0 \quad (\text{A4.17})$$

$$\frac{\partial L}{\partial \psi_t} = -\delta (\sigma_\varepsilon^2)^{-1} (\pi_t + z_t) E_t \mu_{t+1}^5 + \delta E_t \mu_{t+1}^8 = 0 \quad (\text{A4.18})$$

From equation (A4.9) and (A4.12) we have and $E_t \mu_{t+1}^2 = 0$ and $\mu_t^4 = E_t \mu_{t+1}^4 = 0$ respectively. Then, from (A4.11) we see that $\varpi_t E_t \mu_{t+1}^3 = 0$. Using, this information (A4.14), (A4.15) and (A4.10) simplify to

$$\begin{aligned} &-\pi_t - \mu_t^1 + \delta E_t \mu_{t+1}^1 \\ &-\delta \psi_t (\sigma_\varepsilon^2)^{-1} E_t \mu_{t+1}^5 + \delta \varpi_t p_t E_t \mu_{t+1}^7 = 0 \end{aligned} \quad (\text{A4.14}')$$

$$\begin{aligned}
& -\mu_t^2 + \delta E_t \mu_{t+1}^1 & (A4.15') \\
& -\delta \psi_t (\sigma_\varepsilon^2)^{-1} E_t \mu_{t+1}^5 + \delta \varpi_t p_t E_t \mu_{t+1}^7 = 0
\end{aligned}$$

$$-\mu_t^3 + \delta E_t \mu_{t+1}^3 = 0 \quad (A4.10'')$$

Since we are dealing with the case of a non-zero gain, (A4.11) implies $E_t \mu_{t+1}^3 = 0$. Then (A4.16) simplifies to

$$E_t \mu_{t+1}^6 + (\pi_t + z_t) p_t E_t \mu_{t+1}^7 = 0 \quad (A4.16')$$

From equation (A4.13) we have $\mu_t^5 = \mu_t^6$, so that $E_t \mu_{t+1}^5 = E_t \mu_{t+1}^6$. We can then rewrite (A4.16') as

$$E_t \mu_{t+1}^5 = -(\pi_t + z_t) p_t E_t \mu_{t+1}^7 \quad (A4.16'')$$

Using (A4.16'') in (A4.14') and (A4.15') we get

$$-\pi_t - \mu_t^1 + \delta E_t \mu_{t+1}^1 + \delta p_t [\psi_t (\sigma_\varepsilon^2)^{-1} (\pi_t + z_t) + \varpi_t] E_t \mu_{t+1}^7 = 0 \quad (A4.15''')$$

$$-\mu_t^2 + \delta E_t \mu_{t+1}^1 + \delta p_t [\psi_t (\sigma_\varepsilon^2)^{-1} (\pi_t + z_t) + \varpi_t] E_t \mu_{t+1}^7 = 0 \quad (A4.15''')$$

Now it can easily be seen that the term in square brackets appearing before $E_t \mu_{t+1}^7$ is zero by definition. To see this note that the constraints containing the Kalman gain κ_{t+1} (ie (A4.5) and (A4.4)) imply that $\psi_t (\sigma_\varepsilon^2)^{-1} (\pi_t + z_t) = -\varpi_t$. With this result equations (A4.14''') and (A4.15''') will collapse to

$$-\pi_t - \mu_t^1 + \delta E_t \mu_{t+1}^1 = 0 \quad (A4.14''''')$$

$$-\mu_t^2 + \delta E_t \mu_{t+1}^1 = 0 \quad (A4.15''''')$$

These equations correspond with the first order conditions (A2.8) and (A2.9) respectively for the case of perfect knowledge (see Appendix 2).²⁹

Hence, the first order condition is

$$E_t \pi_{t+2} = 0 \quad (A3.6)$$

²⁹ There $\mu_t^2 = 0$ as we have only one constraint, formulated in terms of the inflation *forecast* $x_t = E_t \pi_{t+1}$ rather than in terms of the actual inflation rate, and the output *forecast* $E_t z_{t+1}$ becomes the (indirect) control.

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