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## Monetary policy and data uncertainty

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## Abstract

One of the problems facing policymakers is that recent releases of data are liable to subsequent revisions. This paper discusses how to deal with this, and is in two parts. In the normative part of the paper, we study the design of monetary policy rules in a model that has the feature that data uncertainty varies according to the vintage. We show how coefficients on lagged variables in optimised simple rules for monetary policy *increase* as the relative measurement error in early vintages of data *increases*. We also explore scenarios when policymakers are uncertain by how much measurement error in new data exceeds that in old data. An optimal policy can then be one in which it is better to assume that the ratio of measurement error in new compared to old data is larger, rather than smaller. In the positive part of the paper, we show that the response of monetary policy to vintage varying data uncertainty may generate evidence of apparent interest rate smoothing in interest rate reaction functions: but we suggest that it may not generate enough to account for what has been observed in the data.

## Summary

The data policymakers use to assess the state of the economy are often uncertain proxies for the things they really want to know about. Data releases referring to the most recent periods contain the most signal about the future for policymakers, but typically also contain the most noise. Many data are revised over time, and improved in the process. Those that are not revised are still uncertain, but over time other corroborative evidence arrives that can help us interpret them. We ask how policy should be designed in the face of this kind of data uncertainty. What if policymakers do not know how much variation there is in data uncertainty over time, or over vintages? We also ask whether the response of policy to what we term time variation in data uncertainty, or more properly variation across vintages, can account for the observation that interest rates seem to move more sluggishly in response to news than most models would predict they should.

We present a model that allows us to study variation in measurement error across data vintages. In our model, there are two endogenous variables the central bank has to measure: inflation, and the output gap. In the United Kingdom, and in many other countries, inflation data typically do not get revised, and therefore the measurement error in current period inflation data are (improvements in survey methods aside) the same as that in old data. Output data, however, are revised, and it is likely that early releases of output are less well measured than the revised estimates that succeed them. Our model is a metaphor for this world: inflation data are always perfectly measured, but output gap data become better measured over time.

We make three observations. First, we examine simple optimised rules for monetary policy: these rules are based on current and past-dated inflation and output data. The optimal coefficients change as the amount of noise in the output gap data increases, and as the measurement error in new data increases relative to older data. Intuitively, the more measurement error there is in the output gap data, and the worse current data are relative to lagged data, optimised simple rules put more weight on inflation compared to output gap terms; and more weight on lagged output gap terms relative to current ones.

Second, we note that an econometrician who tries to study the behaviour of central bank policy rates – but is unaware that central bank rates are designed to cope with data uncertainty – will

conclude that interest rates move too sluggishly in response to news. But it is likely that vintage variation in measurement error alone cannot account for the amount of interest rate smoothing seen in the data.

Finally, we explore the effects on policy of uncertainty about noise in new data compared to that in older data. In the face of this lack of knowledge robust policies err on the side of assuming more vintage variation in measurement error, rather than less. This is an interesting theoretical result, but it could also have a practical angle: the apparent ‘excess’ smoothing in observed policy rates may reflect a robust response to an unknown degree of variation in measurement error across different vintages of data.

## 1 Introduction

Most recent data releases tend to be subject to subsequent revisions. This paper studies how this fact affects the design of monetary policy; and how ignoring it may colour our interpretation of time-series studies that attempt to describe past central bank behaviour.

Our laboratory is a calibrated rational expectations IS/AS model in which both the output gap and inflation display persistence. We assume that inflation data do not get revised, and therefore the measurement error in current period inflation data are (improvements in survey methods aside) the same as that in old data. Output data, however, are measured imperfectly, and it is likely that early releases of output are less well measured than the revised estimates that succeed them. We assume that the three output gap variables relevant for the monetary authority in our model are the contemporaneous, first and second lags of the output gap. We also assume that measurement error varies across vintages: the best measured is the second lag of the output gap, while the least well measured is the current output gap.

Using this laboratory, we come to four conclusions. (1) We show how increasing the noise in recent output gap data relative to lagged output gap data leads the monetary authority to put less weight on that more recent data. (2) We show how a monetary policy maker uncertain about the degree of variation in measurement error across vintages is safest assuming more measurement error rather than less: policy rules<sup>(1)</sup> are derived on the assumption that recent data are less well measured than older data do better in the event that this assumption is incorrect than do policy rules based on assuming no vintage dependence of measurement error when in reality the reverse is true. (3) We illustrate how an econometrician ignorant of the fact that past central bank behaviour is based on responding optimally to vintage variation in measurement error will detect an apparent tendency for interest rates to be serially correlated. (4) However, we show that vintage variation in measurement error cannot alone account for the amount of interest rate inertia recorded in empirical cross-country studies of policy rules. Such studies find coefficients of lagged interest rates in policy rules of the order of 0.9. We cannot generate coefficients greater than around 0.5, and even these are based on assuming that measurement error in recent output gap data is implausibly large relative to that in older data.

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(1) This is a theoretical assumption and not intended to claim that the Bank of England or any other authority follows such a rule.

The novelty of our contribution derives mainly from results (2) and (4) above. To make our contribution precise, it is worth setting out the lines of thought in previous work that this paper relies on, and the results in our paper that are anticipated by others.

The first and most basic building block for our paper is that information important for monetary policy is measured with error. Orphanides (2001) constructs an estimate of Fed views of the output gap from official records and compares them to estimates possible with the benefit of hindsight afforded by more recent data and methods. Real-time estimates of the output gap deviate from today's estimate of the truth by 2.6%, on average (Orphanides and van Norden (2002)). They illustrate the errors made in estimating the output gap that come from filtering. This paper distinguishes filtering errors from those deriving from mismeasurement of output itself. This latter source of error has been inferred by extent of revisions to first estimates of output: by Orphanides and van Norden for the United States, by Coenen, Levin and Wieland (2005) for the euro area, and by Castle and Ellis (2002) for the United Kingdom. Kapetanios and Yates (2004) propose using a model of the process of data collection that gives rise to revisions to extract a measure of the uncertainty in output. The measurement error in inflation data has received much less attention, most likely because the inflation rates that are used in explicit inflation mandates tend not to be revised.<sup>(2)</sup> What work there is has sought to quantify not the stochastic nature of inflation measurement errors, but the long-run, mean downward bias in inflation rates that derive from their failure to properly account for improvements in quality, or the effect of new good replacing old ones in the typical consumption basket, and other sources. The key reference here is the Boskin Report for the United States.

A second building block for our paper is that measurement errors in output gap data display what we will term as vintage variation. Specifically, the more recent the time period for which we try to measure the output gap, the less well we measure it. This is inferred from the tendency for revisions to output data to cumulate over time by, among others, Orphanides and van Norden (2002), Coenen *et al* (2005) and Castle and Ellis (2002). Vintage variation in measurement error in output data is derived from their model of the statistics agency by Kapetanios and Yates (2004). Orphanides, Porter, Reifschneider, Tetlow and Finan (2000) stress that filtering induces vintage variation in output gap estimation. These estimates rely on estimating potential output by taking

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(2) GDP deflator data are revised, of course, as data on GDP itself are revised. But these data are typically neither mentioned in explicit inflation mandates, nor understood to be the focal point for monetary policy of those central banks without such mandates. (Not least because they are assumed to be measured less well than the CPI data.)



what are essentially centred moving averages of actual output. These estimates are most poor for the end-points of the series, including of course, the most recent data.

Many papers have explained what monetary policy should do about data uncertainty. The notion that noise in data leads to them having less weight in the policymakers' optimal estimate of the state of the economy is expressed formally in Swanson (2004), and Svensson and Woodford (2003). Orphanides and Williams (2002) and Orphanides *et al* (2000) demonstrate that policymakers uncertain about the output gap should follow rules that respond to *changes* in the output gap. Smets (2002) explains the welfare benefits of mandates for central banks that place extra emphasis on inflation stabilisation at the expense of output stabilisation when the output gap is measured with error.

Our paper focuses on the effect of vintage dependence in data uncertainty on monetary policy design, and to our knowledge there are two other papers that deal with this phenomenon. The first is Coenen *et al* (2005). That paper seeks to establish the usefulness of money as an indicator variable for monetary policy. The extent of and vintage dependence in measurement error is inferred from historical data on how much early vintages are revised. Money is therefore observed to be better measured than output data, and since the revisions are smaller, the amount by which measurement error falls as a vintage matures is also less. The second paper, and the one most closely related to our own, is Aoki (2003). In this paper, the policymaker observes the current value of the output gap with error, but the lagged value of the output gap perfectly. All inflation data, contemporaneous or otherwise, are measured perfectly. Aoki illustrates how an econometrician who does not allow for the monetary policy maker's optimal response to vintage dependence in the measurement of the output gap may wrongly infer that the central bank is engaged in interest rate smoothing.

Our contribution relative to this previous work is now a little clearer. We offer a model of vintage dependence that is more realistic: to repeat, we assume that although the measurement error in the output gap declines as a vintage matures, it never disappears entirely (as in Aoki (2003)). Second, we vary the degree of vintage dependence and illustrate the effect of doing this on the weights placed on inflation and output gaps in simple rules. Third, we illustrate that assuming more rather than less vintage dependence offers a degree of robustness when the true extent of vintage dependence is unknown. And fourth, we observe that Aoki's conjecture that improperly treated

vintage dependence in measurement error could account for apparent interest rate smoothing in estimated policy reaction functions cannot be its sole cause. A minor feature of our contribution is that we experiment with two alternative models of measurement error. The first comes from Kapetanios and Yates (2004) and assumes that successive vintages of the output gap can be described as a sequence of independent random draws on the true output gap. The second is taken from Coenen *et al* (2005) and models the earliest vintage of the output gap as a variable that includes a number of independent random errors that are individually purged from successive vintages.

## 2 The model

### 2.1 The economy

We work with a variant of a model for monetary policy analysis familiar from the work of Rotemberg and Woodford (1997) and McCallum and Nelson (1999). The economy is described by two equations. The demand side of the economy is given by:

$$y_t = \alpha_1 E_t y_{t+1} + (1 - \alpha_1) \sum_{i=1}^2 y_{t-i} - \alpha_2 (r_t - E_t \pi_{t+1}) + u_t \quad (1)$$

where  $y_t$  is output,  $\pi_t$  inflation,  $E_t$  denotes expectations conditional on information at time  $t$ ,  $r_t$  is the nominal interest rate, the instrument of the central bank,  $u_t$  is a demand shock, and the  $\alpha$ 's are parameters. All variables are written as the percentage deviations from steady-state values. This equation says, in words, that output is related to expected future output, and a distributed lag of past output. The presence of backward-looking terms can be justified here by appealing to habit formation in consumption: see, for example, Fuhrer (2000).<sup>(3)</sup>

The second equation is an inflation or aggregate supply equation, written as:

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(3) Note that the most common form of consumption function derived from a model of habit persistence has only one lag on the right-hand side. But there is nothing in the logic of the habit persistence model to rule out *a priori* the possibility that there may be more lags. Indeed, in Fuhrer (2000) the reference value for consumption has potentially infinite memory. The contributions in this paper do not rest on there being more lags, as will hopefully become clear, but the results are more clearly drawn out when there are. For those readers who prefer the 'one lag' consumption function, our analysis has an alternative interpretation; that policymakers are forced to find an optimal indicator of the first lag of output, using combinations of direct observations on the first lag, and observations on the second lag, and then have to choose the optimal weight to put on each.

$$\pi_t = \beta_1 E_t \pi_{t+1} + (1 - \beta_1) \pi_{t-1} + \beta_2 y_t + g_t \quad (2)$$

where  $g_t$  is a cost-push shock, and the  $\beta$ s are parameters. The observation that inflation is sticky ( $0 < \beta_1 < 1$ ) has been a focus of research at least since Fuhrer and Moore (1995), Roberts (1995) and Roberts (1997). Recently, researchers have interpreted an equation like this as being the result of the presence of a portion of firms who use rules of thumb to update prices in line with lagged inflation (see, for example, Galí and Gertler (1999) and Smets and Wouters (2003)).

The parameter values used in our simulations were as follows:

**Table A: Benchmark parameter values**

Output		Inflation		Preferences	
$\alpha_1$	0.60	$\beta_1$	0.60	$\gamma$	0.15
$\alpha_2$	0.15	$\beta_2$	0.20		
$\rho^u$	0.10	$\rho^g$	0.10		
$\sigma_u$	0.65	$\sigma_g$	0.70		

By way of comparison, Smets (2003) estimates a similar model for the euro-area economy, using annual data, with GMM, over the period 1977-97 and obtains a parameter set as follows:

$$\{\alpha_1 = 0.56, \alpha_2 = 0.06, \sigma_u = 0.65, \beta_1 = 0.52, \beta_2 = 0.18, \sigma_g = 0.7\}$$

A quick glance at other estimates reveals a range for  $\alpha_2$  range from 0.06 (Smets (2003)) to 6 (Rotemberg and Woodford (1997)). Turning to our inflation equation, Rudebusch (2002a) concludes that a plausible range would be from 0.4 to 1 for  $\beta_1$ .

### 3 The measurement model

In this economy, the central bank observes inflation perfectly, and the output gap with error. The variance of the error in observing the output gap depends on how much time has elapsed since the data were published. We assume that the central bank never observes the truth – which is surely the case in reality. Typically, GDP releases are subsequently revised. Assuming that the agencies that publish them collect new and useful information about already released data, we can deduce that later releases of GDP are better measured than earlier releases. For this reason, estimates of the unobserved output *gap* will be worse, the newer the vintage.<sup>(4)</sup> Regardless of whether the statistics agency refines its estimates of output, vintage variation in measurement error may also result from procedures used to extract estimates of the unobserved output gap, as Orphanides and van Norden (2002) point out.

We can never know how much better older data are than new, since we never observe the true quantities to compare to the estimates released at different times. We draw two conclusions from this. First, it seems important to study how policy could be designed in the face of an unknown degree of vintage variation in data uncertainty. Second, it is important to allow for some alternatives in how we model the amount by which data uncertainty depends on the vintage.

We assume that the form and size of the measurement error ( $\varepsilon_i$ ) is described as follows:

$$\begin{aligned}y_{t|t} &= y_t + \varepsilon_0 \\y_{t|t+1} &= y_t + \varepsilon_1 \\y_{t|t+2} &= y_t + \varepsilon_2\end{aligned}\tag{3}$$

where  $y_{t|t}$  is the estimate of  $y_t$  published at time  $t$ , and the  $\varepsilon_i$  are white noise error terms, with finite variances, uncorrelated with each other.<sup>(5)</sup>

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(4) Note that we do not consider mismeasurement of potential output, but assume that it is perfectly measured.

(5) In other words, this model abstracts from the possibility that errors may be serially correlated, which is a feature built into Orphanides and van Norden (2002), Rudebusch (2001) and Coenen *et al* (2005).

We experiment with three models that implement our chosen assumption that the variance of the measurement error for ‘new’ data is greater than that for old. Our two variants are as follows. Our first variant is related to the model in Kapetanios and Yates (2004):

$$\begin{aligned} \text{Var}(\varepsilon_2) &= \sigma^2 & (4) \\ \text{Var}(\varepsilon_1) &= (1 + i)\sigma^2 \\ \text{Var}(\varepsilon_0) &= (1 + i)^2\sigma^2 \end{aligned}$$

This model says that the variance of the measurement error in a data point released in some period  $t$  is  $1 + i$  times that in data released one period previously. We will refer to this as the ‘power multiple’ model.

In our second variant measurement errors are serially correlated.<sup>(6)</sup> In the power multiple model a statistics agency publishes revisions as it receives information from sequential, random surveys. Coenen *et al* (2005) suggest an alternative, described below.

$$\begin{aligned} y_{t|t} &= y_t + \varepsilon_{t|t+2} + \varepsilon_{t|t+1} + \varepsilon_{t|t} & (5) \\ y_{t|t+1} &= y_t + \varepsilon_{t|t+2} + \varepsilon_{t|t+1} \\ y_{t|t+2} &= y_t + \varepsilon_{t|t+2} \end{aligned}$$

In period  $t$  the statistics agency publishes an estimate of  $y_t$  denoted  $y_{t|t}$ . In period  $t + 1$ , the agency publishes a new release, equal to the old release less an error in the period  $t$  release  $\varepsilon_{t|t}$ .

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(6)We are grateful to Andy Levin for suggesting these experiments to us.

(This notation can therefore be written in words as ‘the error in the estimate of  $y_t$  that is removed in all estimates following those published in period  $t$ ’.) In period  $t + 2$ , a new release is published, equal to the  $t + 1$  release less an error in that release  $\varepsilon_{t|t+1}$ . We assume that  $\varepsilon_{t|t+2}$ ,  $\varepsilon_{t|t+1}$ ,  $\varepsilon_{t|t}$  are uncorrelated, but note that the total errors in successive estimates of  $y_t$ ,  $y_{t|t} - y_t$ ,  $y_{t|t+1} - y_t$  and  $y_{t|t+2} - y_t$  will be correlated with each other.

We adopt the power multiple model to relate the variances of the errors in  $y_{t|t}$ . We want to do so in a way that allows us to control the ratio of the variances in the measurement error in observations on  $y_{t|t}$ ,  $y_{t-1|t}$ ,  $y_{t-2|t}$  – the three output-gap variables that enter the monetary authority’s policy rule – such that the variances are related thus:

$$\text{var}(y_{t|t} - y_t) = (1 + i)\text{var}(y_{t-1|t} - y_t) = (1 + i)^2\text{var}(y_{t-2|t} - y_t) \quad (6)$$

This will enable us to make computations that hold these ratios equal to those in our previous model of revisions, and illuminate the differences that come from allowing for the serial correlation in measurement errors of successive vintages. To do that we assume:

$$\text{var}(\varepsilon_{t|t}) = (i + i^2)\sigma^2, \text{var}(\varepsilon_{t|t+1}) = i\sigma^2, \text{var}(\varepsilon_{t|t+2}) = \sigma^2 \quad (7)$$

where  $\sigma^2$ , as before, is the variance in the measurement error of the oldest piece of data ( $y_{t-2|t}$ ).

Importantly, note that we are assuming that firms and households have all the information they need to take their decisions, including the information necessary to form rational expectations of what the central bank will do (given the measurement problem *it* faces). In this respect we are following Aoki (2003) and Svensson and Woodford (2004).

### **3.1 The policymaker’s problem**

We consider a class of policy rules open to the central bank of the following form:

$$r_t = f_1\pi_t + f_2\pi_{t-1} + f_3y_{t|t} + f_4y_{t-1|t} + f_5y_{t-2|t}, \quad f_i > 0 \quad (8)$$

We assume that policymakers solve the following problem:

$$\text{Min } E_t \sum_{\tau=0}^{\infty} \beta^\tau L_{t+\tau} \quad (9)$$

where the period loss function is modelled as

$$L_t = \pi_t^2 + y_t^2 + \gamma \Delta r_t^2 \quad (10)$$

As the discount factor  $\beta$  approaches unity, it can be shown that the loss becomes proportional to the unconditional expected value of the period loss function, that is

$$L_t = \text{Var}(\pi_t) + \text{Var}(y_t) + \gamma \text{Var}(\Delta r_t) \quad (11)$$

In words, policymakers, by choice of the coefficients on the arguments in the class of simple rules above, (by choice of  $f_i$ ), minimise the expected sum of squared deviations of inflation from a zero target, of the output gap, and of changes in nominal interest rates. Policymakers recognise that they receive noisy data, and attempt to remove the noise component, before formulating policy, using the measurement models above to provide ‘optimal estimates’ (filtered information) to the policy problem. We include a term in nominal interest rates so that the coefficients on the arguments in the simple rule are plausibly small (we assume  $\gamma = 0.15$ ).<sup>(7)</sup> We will report too experiments to demonstrate that our conclusions in this respect are not sensitive to our choice of  $\gamma$ . Note that policymakers minimise a loss function involving the true output gap,  $y_t$ . In particular, when optimising rules the policymaker uses (different) measurement models described above to account for real-time output gap uncertainty. We analyse two cases. First, there is no uncertainty surrounding a particular measurement model; and second, we evaluate the robustness of the rules to uncertainty that encompasses policymakers’ estimate about the degree of measurement error in new data. Furthermore, we assume that policymakers can commit to the optimised simple rule.<sup>(8)</sup>

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(7) Later in the paper we explore how failing to account for policymakers’ responses to vintage variation in data uncertainty can generate apparent smoothing in interest rates: this smoothing is *over and above* that deriving from the interest rate term in the objective function.

(8) Solutions are obtained using algorithms described in Söderlind (1999). We used the optimisation package in Gauss to search for the loss-minimising coefficients.

## 4 Results

### 4.1 Optimised simple rules and vintage varying data uncertainty

We turn next to illustrate how the coefficients in these optimised simple rules change as we experiment with variants of the measurement model. To provide a benchmark, we present the optimised simple rule under the assumption that there is no measurement error in the output gap. This is given by

$$r_t = 1.43\pi_t + 1.69\pi_{t-1} + 2.68y_{t|t} + 1.90y_{t-1|t} + 0.41y_{t-2|t} \quad (12)$$

To give a flavour of how our characterisation of data uncertainty affects policy, we can contrast this rule with an arbitrarily chosen version of our power multiple measurement model.

$$r_t = 1.65\pi_t + 1.35\pi_{t-1} + 1.05y_{t|t} + 1.01y_{t-1|t} + 0.99y_{t-2|t}; \quad i = 1, \sigma = 0.5\% \quad (13)$$

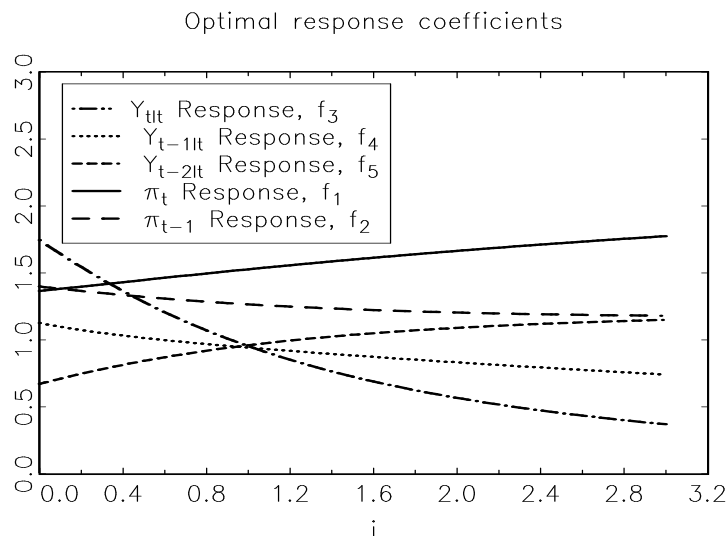
The optimised coefficients in the two rules differ markedly. The coefficient on inflation is higher in the vintage varying uncertainty case, which is not surprising; optimal policy puts more weight on inflation information, which is measured perfectly. Another key difference is that in the no-uncertainty case, the coefficient on the current output gap is over twice the coefficient on output lagged two periods, whereas in the presence of measurement errors the coefficients are almost equal. In other words, the fact that measurement error is smaller in older data leads optimal policy to put more weight on older data, relative to the weight on data of a more recent vintage.

We proceed from this illustration to set up a more systematic class of experiments that cover our different measurement models.

Chart 1 records results from our power multiple measurement error model. We increase  $i$  along the x-axis, for a given variance of the primitive measurement error  $\sigma$  (set equal to 0.5). The y-axis records the values of optimised coefficients attached to different data in the policy rule. As  $i$  increases, the ratio of measurement error in the current output gap to that in the output gap two periods ago increases by the square of  $1 + i$  (etc). As we increase  $i$ , we can see that the optimised



**Chart 1: Power multiple model:  $\sigma = 0.5\%$**



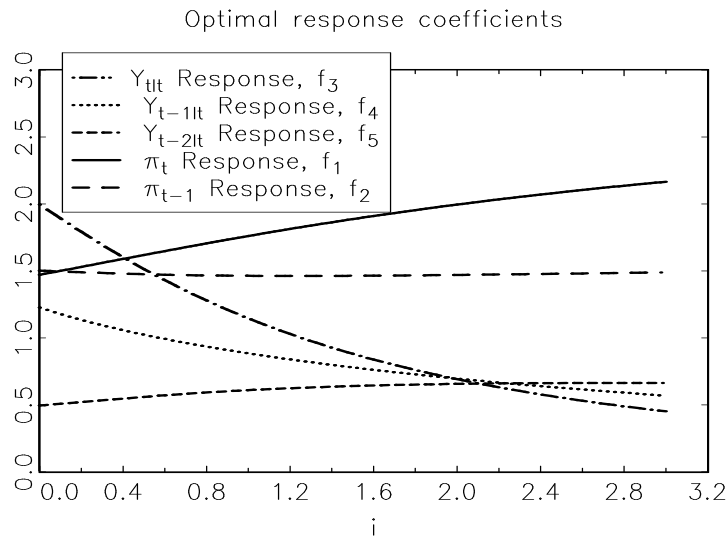
coefficients on the inflation terms increase. The optimised coefficients on current and the one period lag of the output gap decrease. The coefficient on the output gap two periods ago increases, even though the standard deviation of the measurement error in the two period ago output gap (which is  $\sigma = 0.5\%$ ) is not affected by increasing  $i$ .

Chart 2 records the equivalent set of results using our second model of revisions.

Certain broad features of the results are preserved across the two models. First, there is the tendency for the sum of coefficients on inflation variables to increase relative to the sum of coefficients on the output gap variables. In the computations for Chart 2, as in Chart 1, this is brought about by the value of the coefficient on today's inflation,  $\pi_t$ , rising, and the coefficient on today's estimate of today's output gap,  $y_{t|t}$ , falling. A second similarity is that as we increase  $i$  the optimised rules put more weight on older output gap data compared to newer output gap data. One minor quantitative is this: in these computations policy puts less weight on output gap data two periods ago, and more weight on inflation, compared to those in Chart 1.

To re-state briefly the results of this section: the older data is better measured than new data, the less weight optimal policy – in the sense we explore it – places on new data. These results are akin to those in Harrison, Kapetanios and Yates (2005). That paper constrains a forecaster to use

**Chart 2:**  $\sigma = 0.5\%$



the same number of lags as the DGP. An optimal forecast subject to that constraint places weights on the different lags that are functions of the relative measurement error in different lags. They are also consistent with the reported effects of data uncertainty on optimal policy set out in Aoki (2003).

We have observed that the weights policymakers attach to the arguments in the simple rules we have studied vary as we change the ‘term structure’ of measurement error attached to different vintages of the output gap. The signal-extraction/estimation problem, the problem of forming an optimal estimator of the current state of the economy, is not invariant to these disturbances. Changing the relative measurement error attached to different vintages of the output gap causes policymakers to change the weights put on the output gap terms in the (constrained) optimal estimator of the state. The breach of the certainty equivalence principle comes from the fact that policy is constrained to follow a simple Taylor-like rule.

#### 4.2 *Data uncertainty and apparent interest rate smoothing*

In this section we illustrate how vintage variation in data uncertainty, and the optimal response to this by policymakers, could generate evidence of apparent interest rate smoothing in reduced-form regressions for central bank interest rates. We begin by recalling some of the intellectual

background to this exercise.

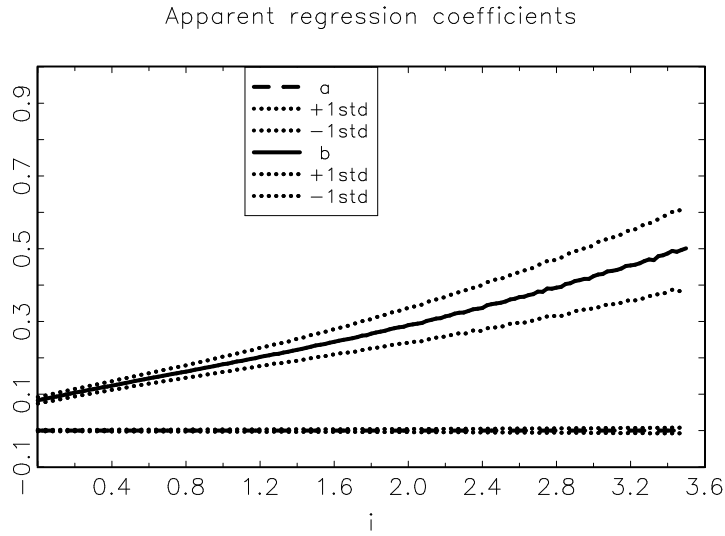
Many studies have observed that central bank interest rates appear to be serially correlated. To take one example, Clarida, Gali and Gertler (1998) find that the coefficient on lagged interest rates in estimated equations for central bank rates varies from between 0.87 and 0.95 (they estimate equations for the United States, Germany, Japan, France, Italy and the United Kingdom). Related observations have been made by Judd and Rudebusch (1998), Sack (2000), Sack and Wieland (2000), Rudebusch (2002b), Amato and Laubach (1999) and many others. Several reasons have been put forward to explain this phenomenon. Blinder (1998) suggested that interest rates may respond only gradually to news because of the inertia generated by a committee-based decision-making process: it may take time to build a consensus in a committee for an interest rate move. Goodfriend (1991) suggested that central banks might wish to commit to making interest rates serially dependent in order to increase the effect of a change in short rates on long rates, and therefore on aggregate demand. The argument was later formalised by Woodford (2003), who pointed out that doing this would enable policymakers to reduce the risk of encountering the zero bound to interest rates for a given inflation target. Woodford (2000) argued that policymakers unable to commit to interest rate strategies may be able to replicate the behaviour of a hypothetical central bank that could by following an interest rate policy that is ‘history-dependent’, of which a policy that sets interest rates as a function of past interest rates is one example. Sack (2000) observed that gradual changes in interest rates may be the result of central banks’ optimal response to parameter uncertainty. Rudebusch (2002b) argues that interest rate smoothing is due to the omission from estimated reaction functions of some serially correlated variable to which central banks are in fact responding.<sup>(9)</sup>

We examine the case where the econometrician wishes to investigate apparent interest rate smoothing. She does so unaware that policy is responding optimally to vintage variation in data uncertainty. She seeks to measure the dependence of interest rates on lagged interest rates, controlling for the dependence of interest rates on an optimal nominal interest rate  $r^*$ , one under no data uncertainty, where  $r^*$  is given by:

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(9) The work of Orphanides (2004) alerts us to the danger of reading too much into estimated interest rate rules that do not use the data to which policy makers had access at the time policy decisions were made. Orphanides argues, for example, that the inference in Clarida, Gali and Gertler (2000) that policy became more inflation stabilising after the appointment of Paul Volcker in 1979 is an artifice of using final rather than real-time data. It is conceivable that evidence on apparent interest rate smoothing could be subject to the same critique.

**Chart 3: Power multiple model,  $r_t - r_t^* = a + br_{t-1} + \varepsilon_t$ ;  $\sigma = 0.5\%$**



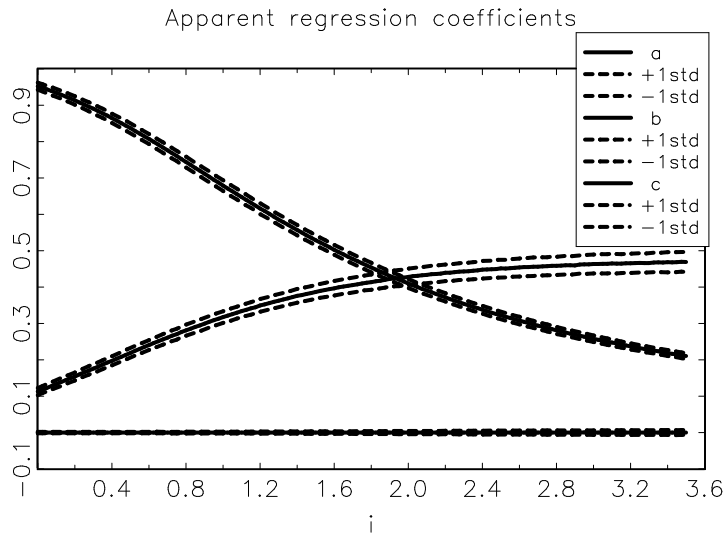
$$r^* = f_1\pi_t + f_2\pi_{t-1} + f_3y_t + f_4y_{t-1} + f_5y_{t-2}$$

(This  $r^*$  itself is one that emerges from the econometrician's calculation of how policy optimises subject to the objective function that involves the term in interest rates. But the dependence of  $r_t$  on  $r_{t-1}$  measured this way is still a coherent concept of excess interest rate smoothing.) The econometrician characterises apparent interest rate smoothing as the dependence of  $r_t$  on  $r_{t-1}$  controlling for its dependence on the terms in  $r^*$ . We explore two ways of doing this.

The first case, in Chart 3, shows the constant and coefficient from a regression of  $r_t - r_t^*$  on  $a + br_{t-1}$ . We simulate the model (with the policymaker conducting policy according to the appropriate optimised rule) for 500 periods. We then run this regression. The charts plot the average of 3,000 such simulated regressions, and record the spread of the regression coefficients. Equations are estimated using simple OLS. As  $i$  increases, that is, as the ratio of the measurement error in newer data relative to older data increases, the interest rate smoothing apparent to the econometrician increases as well.

Note that when  $i$  is zero, the estimated apparent excess interest rate smoothing coefficient ( $b$ ) is not zero. Recall that the econometrician is using an estimate of optimal rates ( $r^*$ ) that assumes

**Chart 4: Power multiple model,  $r_t = a + br_t^* + cr_{t-1} + \varepsilon_t$ ;  $\sigma = 0.5\%$**



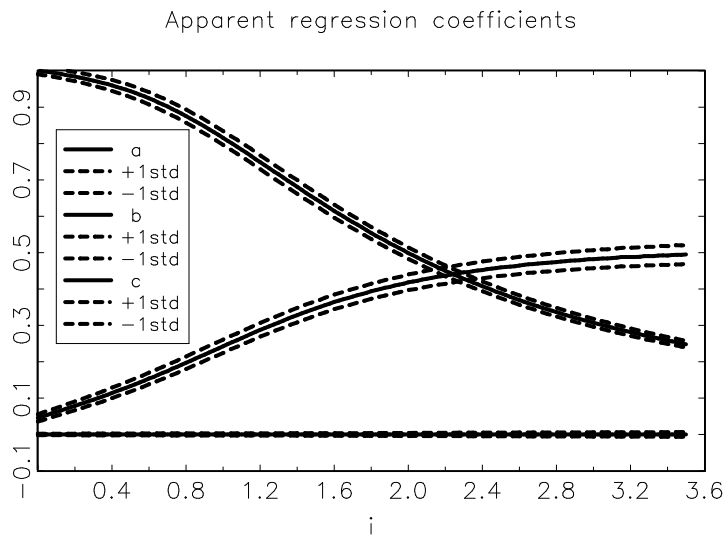
there is no data uncertainty at all. Yet when  $i$  is zero, there is simply vintage invariant data uncertainty in the output gap. Relative to the ‘true’  $r^*$ , which accounts for data uncertainty, the econometrician’s  $r^*$  will put too much weight on output gap data, and too little weight on the (perfectly measured) inflation data. It turns out that  $r_{t-1}$  is correlated with the difference between the two  $r^*$ s.

In the second case, illustrated in Chart 4, we free up the coefficient on  $r_t^*$ , regressing  $r_t$  on  $r_t^*$ , and  $r_{t-1}$ . The results are similar to those in Chart 3. We find that as  $i$  increases, the coefficient on  $r^*$  falls, and the coefficient on  $r_{t-1}$  rises.

Another point to take from these two charts is that if we restrict the coefficient on  $r^*$  the increase in the apparent interest rate smoothing coefficient does not tail off as we increase  $i$ . If we estimate with a free coefficient on  $r^*$  then it does.

These results confirm our findings. As we increase the noise in new data relative to old data (as we increase  $i$ ), the amount of apparent interest rate smoothing increases, and the weight on the conjectured target interest rate decreases. Notice that in this case we generate a degree of apparent interest rate smoothing that is a little greater than before. In Chart 4 the degree of apparent smoothing levels out slightly below 0.5, whereas in Chart 5, which repeats the experiment with the

**Chart 5:**  $r_t = a + br_t^* + cr_{t-1}$ ;  $\sigma = 0.5\%$

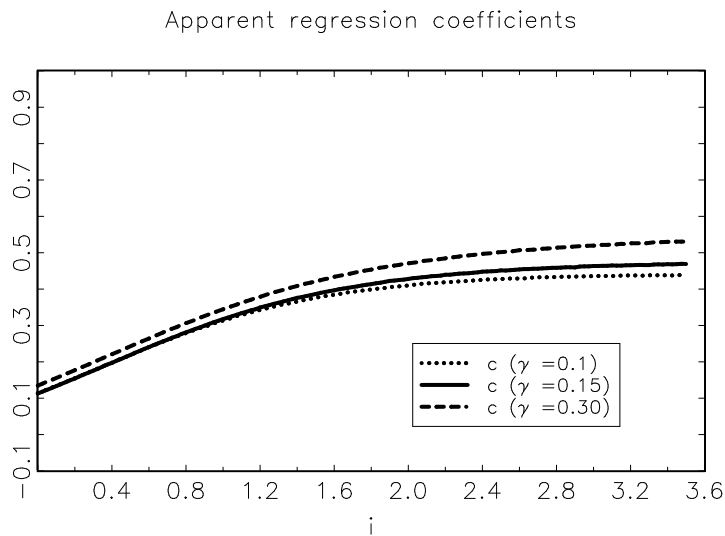


second variant of the measurement model, the apparent coefficient on lagged rates levels out instead at about 0.5. The serial correlation between errors in successive vintages of data in this measurement error model induces marginally higher apparent interest rate smoothing. This, of course, still falls some way short of the values observed in econometric studies.

Recall that our notion of apparent excess smoothing is the dependence of interest rates on lagged interest rates once the dependence of interest rates on optimal rates is controlled for, and that optimal interest rate is computed by the econometrician to be the result of (correctly) assuming the policymaker optimises subject to an objective function that contains a term in the change in interest rates, but (incorrectly) assuming that there is no data uncertainty. That should clarify that our results are not dependent on assuming that the objective function contains a term in the change in interest rates. However, Chart 6 contains some results that confirm this. It plots the regression coefficient  $c$  (as function of  $i$ ) for different values of  $\gamma$ , (the weight on the change in interest rates in the policymaker's objective function) using the power multiple model. As before, as  $i$  increases, so does the amount of apparent interest rate smoothing: the amount by which the apparent interest rate smoothing increases for a given increase in  $i$  (the ratio of the measurement error in new relative to older data) is not affected by our choice of  $\gamma$ .<sup>(10)</sup>

(10) We did the same experiment assuming a level term  $\gamma r_t$  in the loss function rather than the change in the interest rate (ie  $\gamma \Delta r_t$ ). Again, as  $i$  increased, so did the amount of apparent interest rate smoothing. It, however, tailed off around 0.35.

**Chart 6: Power multiple,  $r_t = a + br_t^* + cr_{t-1}$ ;  $\sigma = 0.5\%$**

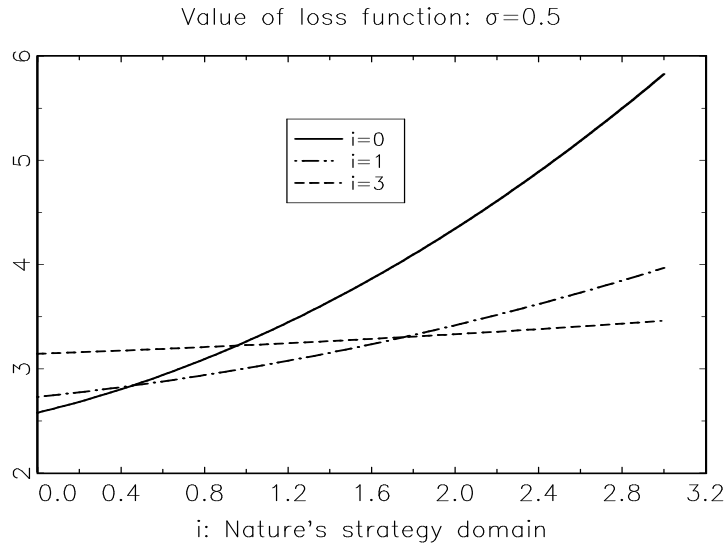


Can vintage variation in measurement error account for the degree of interest rate inertia observed in modern economies? Recall the range of coefficients estimated by Clarida *et al* (1998) that we cited earlier: 0.87-0.95. That range referred to the coefficient in equations with varying specifications, but all of which are sufficiently close to our second equation in Charts 4 and 5 to make the comparison worthwhile. Note that we cannot generate a coefficient on lagged interest rates ( $r_{t-1}$ ) larger than about 0.5. And to get a coefficient of that size, we need that  $i$  is greater than 3.5. When  $i = 3.5$ , the measurement error in the current output gap is 4.5 times that in the output gap one period ago, and over 20 times the measurement error in the output gap two periods ago. Is this plausible? We of course do not observe these ratios, since we do not observe true data on output, let alone on the output gap. But still this number seems too large to us. We conclude at this point that plausible degrees of vintage variation in measurement error cannot account for all the apparent excess interest rate smoothing in empirical studies.

### 4.3 Monetary policy in the face of unknown amounts of data uncertainty

In our final exercise we ask the following question: suppose there is some uncertainty about how much worse newer data are than old. What should policy do? We seek to discover how rules based on different assumptions about the unknown data uncertainty in the economy perform across different realisations. We compute the costs of optimising policy on the assumption that there is

### Chart 7: Power multiple model and robustness



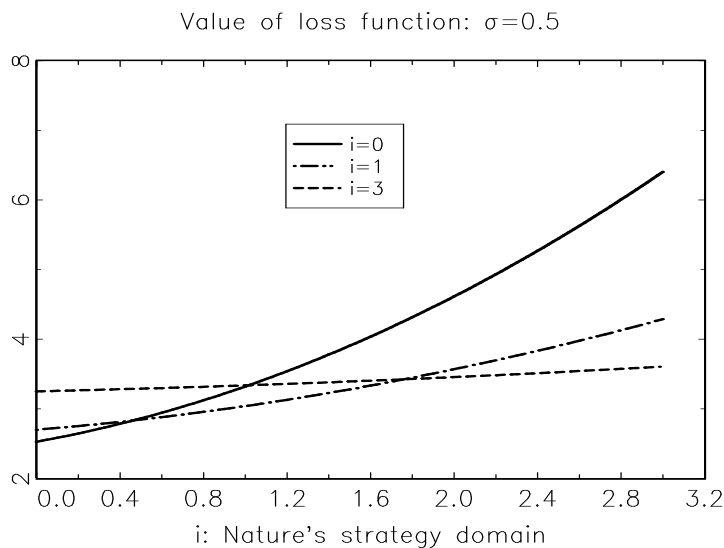
no vintage variation in measurement error, when in reality there is, and compare these costs to the costs of assuming there is vintage variation in measurement error when in reality there is not.

Chart 7 shows the results using the power multiple model. The unknown parameter for policymakers is  $i$ . Each line in the chart plots the losses that accrue when policymakers assume that the world is characterised by some  $i$ . The x-axis records the values of  $i$  that obtain in reality, or, in the language of the min-max literature, the strategy that a malevolent nature adopts to frustrate the policymaker ( $\sigma$  is held fixed at 0.5). Recall that as  $i$  increases, the measurement error in newer data relative to older data increases. The solid line shows losses accruing when policymakers assume that  $i = 0$ , ie that the measurement error in the output gap terms is the same, regardless of their vintage. Naturally, this strategy works best (achieves the smallest losses) when nature ensures that  $i = 0$ : the strategy works best, in other words, when the assumption about reality turns out to be valid. Losses rise steeply as nature's 'choice' of  $i$  becomes more and more positive. The greater the value for  $i$  assumed by the policymaker (the greater the assumed difference between the noise in new versus old data), the more invariant are losses to variations in the strategy by nature. In the face of uncertainty about how much measurement error differs in new compared to old data, policymakers can insure themselves by assuming a high value for  $i$ .

Chart 8 carries out the same experiment using the model with autocorrelated measurement errors.



**Chart 8: Serially correlated measurement errors and robustness**



In this environment, the consequences of wrongly assuming that there is no vintage variation in measurement error are similar to those in the power multiple model. Assuming a high value for  $i$  when nature delivers  $i = 0$  generates relatively large losses.

Our results show that a robust response to an unknown degree of vintage variation can be to assume more rather than less. This is related to the result in Orphanides and Williams (2002). They find that difference rules – rules that have the current interest rate set as a function of lagged interest rates and changes in real variables – perform well in response to an unknown degree of uncertainty in the natural rates of interest and unemployment. In our case, as in theirs, interest rates become more dependent on lagged values variables. (In our experiments interest rates do not become more dependent on lagged interest rates with uncertainty about the uncertainty in data, since we constrain policy not to respond to lagged interest rates when computing the optimised simple rule.)

Recall that in the previous section we noted that it seemed that we would need an implausibly large ratio of the measurement error in new compared to old data to account for the degree of apparent excess smoothing in rates observed in the empirical literature on central bank interest rates. Our results in this section – that a robust policy could be to assume more rather than less vintage variation in data uncertainty – could have a positive interpretation. A proportion of the

apparent excess smoothing we observe could have as its origin the form of data uncertainty investigated here.

## 5 Conclusion

We presented a model in which to study vintage variation in measurement error. In our model, there are two endogenous variables the central bank has to measure: inflation and the output gap. In the United Kingdom, and in many other countries, inflation data typically do not get revised, and therefore the measurement error in current period inflation data are (improvements in survey methods aside) the same as that in old data. Output data, however, are revised, and it is very likely the case that early releases of output are less well measured than the revised estimates that succeed them. Our model is a metaphor for this world; inflation data are always perfectly measured; while output gap data are better measured, the older the data.

We used this model to do three things. First, we characterised how the coefficients on optimised simple rules that involve terms in current and past-dated inflation and output data change as the amount of noise in the output gap data increases, and as the measurement error in new data increases relative to older data. Intuitively, the more measurement error in output gap data, and the worse are current data relative to lagged data, the more optimised simple rules put weight on inflation compared to output gap terms, and on lagged relative to current output gap terms.

Our second task was to see how the optimal response to vintage variation in measurement error could generate apparent interest rate smoothing in reduced-form estimates of interest rate reaction functions. We observed that it could, and the more so, the more vintage variation there was in measurement error (up to a point). Given the parameter values we have chosen for our simulations, it seemed likely that vintage variation in measurement error alone could not account for the amount of interest rate smoothing seen in the data.

We saw that these first two sets of results were broadly robust to using two alternative models of measurement error: one that characterises revisions as arising from a statistics agency conducting sequential random surveys and publishing a revision that weights new information together with old; and one that describes revisions as arising from a statistics agency ‘removing’ errors from an initial data release.

Finally, we explored the effects on policy of there being uncertainty about the degree to which the noise in new data exceeds that in older data. Robust policies in the face of this lack of knowledge err on the side of assuming more vintage variation in measurement error, rather than less. This is an interesting normative result, but it could also have a positive angle: some of the ‘excess’ apparent interest rate smoothing may result from a robust response to an unknown degree of vintage variation in measurement error.

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