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William Greene, Mark N. Harris, Christopher Spencer

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William Greene[1], Mark N. Harris[2], Christopher Spencer[3]
[1] New York University, USA
[2] Bankwest Curtin Economics Centre, Curtin Business School, Australia
[3] Economics Division, School of Business and Economics, Loughborough University, UK.

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Estimating the Standard Errors of Individual-Specific Parameters in Random Parameters Models*

William Greene† Mark N. Harris‡ Christopher Spencer§

Abstract

We consider the estimation of the standard errors of individual-specific parameters calculated *ex post* from a non-linear random parameters model. Our key contribution lies in introducing a simple method of appropriately calculating these standard errors, which explicitly takes into account the sampling variability of the estimation of the model's parameters. To demonstrate the applicability of the technique, we use it in a model of the voting behaviour of Bank of England MPC members. Our results have clear implications for drawing statistical inference on the estimated random parameters.

Keywords: Random parameters, individual-specific parameters, standard errors, voting, Monetary Policy Committee.

JEL Classification: C25

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† New York University, USA.
‡ Curtin University, Perth, Australia.
§ Economics Division, School of Business and Economics, Loughborough University, UK.

1 Introduction

The past decade has seen a rise in the empirical use of random parameter models, especially in economics (see for instance Allenby and Rossi 1998; Revelt and Train 1998; Layton and Brown 2000; Greene 2004; and Train 2009). This is especially so for discrete choice and limited dependent variable (LDV) models; indeed, many 'off-the-shelf' estimators in leading econometric software packages are also available in a random parameters form. The major reason for their popularity is twofold: first, they represent a relatively simple way of introducing unobserved heterogeneity into a model; and, second, due to increased computing power and the development of simulation based estimation, the numerical integration of these unobserved effects out of the likelihood function is relatively quick and easy.

In this paper we show an easy method of how one can provide appropriate estimates of the standard errors of individual-specific random parameters, which takes into account the *sampling variability* of the estimation of the model's parameters. As is subsequently demonstrated in our empirical application, taking into account this phenomenon is not inconsequential, and lends empirical support to Greene (2009), who suggests that by ignoring the sampling variation in the estimation of the original parameters of a discrete choice/LDV model, inaccurate estimates of the coefficients' standard errors will arise.[1] This in turn means that the applied researcher will be unable to make meaningful claims regarding the statistical significance of individual random parameter coefficients.

We propose that our method represents a natural addition to the literature on unobserved heterogeneity: in particular, it is notable that whereas researchers are often interested whether individual (e.g. fixed effects) dummies are statistically significant or not, curiously, the same cannot be said for the statistical significance of random parameters. This should no longer be the case, particularly given the advances in computing power mentioned above. Our contribution may also be of use to applied researchers using panel data sets characterized by a time dimension far greater than, and a unit dimension far smaller than, the "typical small *T*, large *N*" microeconomic panel.[2] As noted in Judson and Owen (1999), "small *N*, big *T*" datasets are often encountered by macroeconomists, although we note that there will invariably be many other situations for which using such datasets is necessary and/or desirable. In this paper, we utilize a "small *N*, big *T*" panel dataset containing Bank of England MPC members' votes on the short-term interest rate for the period August 1997-December 2011. Our application clearly demonstrates the importance of using our suggested technique for the applied researcher.

[1] See Greene (2009), p.E17-53.

[2] Arellano and Bonhomme (2009) observe that in many microeconomic applications, it is of interest to estimate the *distributions* of individual-specific effects. This is especially true for the case of random parameters, and reflects the fact that such literature focuses on panels with small time dimensions and large individual dimensions.

2 A random parameters ordered probit model

We illustrate our suggested approach with an application to a random parameters ordered probit model, although the technique is clearly widely applicable. As a starting point, consider a standard latent regression for the variable of interest (y^*) of the form

$$y_i^* = \mathbf{x}_i'\boldsymbol{\beta} + \varepsilon_i \tag{1}$$

where $\mathbf{x}$ is a set of controls (with no constant term, and of dimension k); $\boldsymbol{\beta}$ is a vector of unknown coefficients and ε is a standard normally distributed random disturbance term. The usual ordered probit (OP) set-up (Greene and Hensher 2010) translates the latent variable into observed y, with $j = 1,\dots,J$ reported ordered outcomes (where J is the total number of outcomes), via the mapping

$$y_i = \begin{cases} 1 & \text{if } y_i^* \leq \mu_0, \\ j & \text{if } \mu_{j-1} < y_i^* \leq \mu_{j,} \ (j = 2, \dots, J-1), \\ J & \text{if } \mu_{J-1} \leq y_i^*, \end{cases} \tag{2}$$

where $\boldsymbol{\mu}$ are the so-called boundary, or threshold, parameters in the OP model. Under the assumption of normality, this translates into the following probabilities for the outcomes:

$$p_i^{OP} = \begin{cases} \Pr(y_i = 1 \mid \mathbf{x}_i) = \Phi(\mu_1 - \mathbf{x}_i'\boldsymbol{\beta}) \\ \Pr(y_i = 2 \mid \mathbf{x}_i) = \Phi(\mu_2 - \mathbf{x}_i'\boldsymbol{\beta}) - \Phi(\mu_1 - \mathbf{x}_i'\boldsymbol{\beta}) \\ \vdots \\ \Pr(y_i = J \mid \mathbf{x}_i) = 1 - \Phi(\mu_{J-1} - \mathbf{x}_i'\boldsymbol{\beta}) \end{cases} \tag{3}$$

where $\Phi(\,.\,)$ denotes the standard normal cumulative distribution function.

Once the full set of probabilities has been specified and given an *i.i.d.* sample from the population of (y_i, $\mathbf{x}_i$) ($i = 1,\dots,N$), the parameters of the model $\boldsymbol{\theta} = (\boldsymbol{\beta}', \boldsymbol{\mu}')'$ can be consistently and efficiently estimated using maximum likelihood, yielding an asymptotically normally distributed estimator. The log-likelihood function is

$$\log L(\boldsymbol{\theta}) = \sum_{i=1}^{N} \sum_{j=1}^{J} d_{ij} \ln[\Pr(y_i = j \mid \mathbf{x}_i)], \tag{4}$$

where d_{ij} is the indicator function, $\mathbf{1}[y_i = j]$. Now, consider augmenting equation (1) with random parameters on all of the $\boldsymbol{\beta}$ coefficients. The random parameters will take the form

$$\boldsymbol{\beta}_i = \boldsymbol{\beta} + \boldsymbol{\Gamma}\mathbf{v}_i \tag{5}$$

where each element of $\mathbf{v}_i$ has mean zero and variance 1. The scaling matrix, $\mathbf{\Gamma}$ is either lower triangular or diagonal (the latter is generally assumed for reasons of parsimony in large k models). The covariance matrix of the random parameters is given by $\mathbf{\Omega} = \mathbf{\Gamma\Gamma}'$, and the 'mean', $\boldsymbol{\beta}$, represents the average effect of the covariates in the population latent regression.

The model can be estimated by the method of maximum simulated likelihood. Conditioned on $\mathbf{v}_i$, the sequence of outcomes for individual i are independent. The contribution to the likelihood function for a group of t observations is the product of the sequence of the OP probabilities corresponding to the observed outcome of $y_i, p_i^{OP}|\mathbf{v}_i$,

$$p_{\boldsymbol{i}}^{\boldsymbol{OP}}|\mathbf{v}_i = \prod_{\boldsymbol{t=1}}^{\boldsymbol{T_i}} \prod_{\boldsymbol{j=1}}^{\boldsymbol{J}} [\Pr(y_{it} = j \mid \mathbf{x}_{it}, \mathbf{v}_i)]^{\boldsymbol{d_{ijt}}}. \tag{6}$$

Note that $\mathbf{v}_i$ enters the probability through (5). The log likelihood function for the sample conditioned on the random effects is

$$\log L(\beta,\mu,\Gamma|\mathbf{v}_1,\ldots,\mathbf{v}_N) = \sum_{i=1}^{N} \log \prod_{t=1}^{T_i} \prod_{j=1}^{J} [\Pr(y_{it} = j \mid \mathbf{x}_{it}, (\boldsymbol{\beta} + \mathbf{\Gamma}\mathbf{v}_i)],$$

and the unconditional log likelihood is obtained by integrating out the random effects, namely

$$\log L(\beta,\mu,\Gamma) = \sum_{i=1}^{N} \log \int_{\mathbf{v}_i} \prod_{t=1}^{T_i} \prod_{j=1}^{J} [\Pr(y_{it} = j \mid \mathbf{x}_{it}, (\boldsymbol{\beta} + \mathbf{\Gamma}\mathbf{v}_i)] f(\mathbf{v}_i)\mathbf{v}_i.$$

Since $\mathbf{v}_i$ is a vector of independent standard normal variables, the joint density is the product of standard normals, so

$$\log L(\beta,\mu,\Gamma) = \sum_{i=1}^{N} \log \int_{\mathbf{v}_i} \prod_{t=1}^{T_i} \prod_{j=1}^{J} [\Pr(y_{it} = j \mid \mathbf{x}_{it}, (\boldsymbol{\beta} + \mathbf{\Gamma}\mathbf{v}_i)] \prod_{k=1}^{k} \phi(v_{ik}) v_{ik}.$$

The expected values in the integrals can be evaluated by simulation. We draw $r = 1, \ldots R$ variates of $\mathbf{v}_i$ from their assumed standard normal distribution[3] and construct the simulated log likelihood function,

$$\log L_S(\beta,\mu,\Gamma) = \sum_{i=1}^{N} \log \frac{1}{R} \sum_{r=1}^{R} \prod_{t=1}^{T_i} \prod_{j=1}^{J} [\Pr(y_{it} = j \mid \mathbf{x}_{it}, (\boldsymbol{\beta} + \mathbf{\Gamma}\mathbf{v}_{ir})]. \tag{7}$$

This now feasible function is maximized with respect to $\boldsymbol{\beta}$, $\boldsymbol{\mu}$, and the elements of Γ. *Ex post*, conditional on the data, individual-specific estimates of $\boldsymbol{\beta_i}$ are computed using

$$\hat{\boldsymbol{\beta}}_i = \hat{E}[\boldsymbol{\beta}_i \mid data_i, \boldsymbol{\beta}, \boldsymbol{\mu}, \Gamma] = \frac{\frac{1}{R}\Sigma_{r=1}^{R}\left(\hat{\boldsymbol{\beta}} + \hat{\Gamma} v_{ir}\right)\left(\Pi_{t=1}^{T_i} p_{it}^{OP} \mid \mathbf{v}_{ir}\right)}{\frac{1}{R}\Sigma_{r=1}^{R}\left(\Pi_{t=1}^{T_i} p_{it}^{OP} \mid \mathbf{v}_{ir}\right)} = \frac{1}{R}\sum_{r=1}^{R} w_{ir}\hat{\boldsymbol{\beta}}_{ir} \tag{8}$$

[3] In estimation we use Halton sequences (Train 2009) of length $R = 1{,}000$.

(See Train 2009; Greene 2009) where $data_i$ denotes all the information at hand about individual i. Note that these are not actual estimates of $\boldsymbol{\beta_i}$, but are estimates of the conditional mean of the distribution of the random parameters.

3 Standard errors of individual-specific parameters

Just as these estimates of $\widehat{\boldsymbol{\beta}}_{\boldsymbol{i}}$ are likely to be of interest to researchers, clearly so will inference on them. To this end, Greene (2009) suggests estimating the standard deviation of this distribution as

$$\sqrt{\frac{\frac{1}{R}\sum_{r=1}^{R}\left[\left(\hat{\hat{\beta}} + \mathbf{v}_{ir}\right)^2\left(\prod_{t=1}^{T} p_i^{OP}(\mathbf{v}_r)\right)\right]}{\frac{1}{R}\sum_{r=1}^{R}[\prod_{t=1}^{T} p_i^{OP}(\mathbf{v}_r)]} - \left(\widehat{\boldsymbol{\beta}}_{\boldsymbol{i}}^{*}\right)^2} \qquad (9)$$

On the basis of using a mean plus/minus two standard deviations, equation (9) can be utilized to construct approximate 95 percent confidence intervals for $\boldsymbol{\beta_i}$. There are, however, two shortcomings with this approach. First, it takes no account of the sampling variability of the parameter estimates. Second, the variance of expression (9) turns out to be an estimator of the *conditional variance*, namely

$$\hat{V}_i = \widehat{Var}[\boldsymbol{\beta}_i \mid data_i, \boldsymbol{\beta}, \boldsymbol{\mu}, \Gamma].$$

More specifically, it is an estimator of the variance of the conditional distribution of $\beta_i|data_i$, and *not* an estimator of the sampling variance of the estimator of $E[\beta_i|data_i]$. There is no necessary comparison of these two quantities. As mentioned at the outset of this paper, Greene (2009) also speculates that confidence intervals based around such measures are likely to be inaccurate as they do not take into account the sampling variation involved in the estimation of $\widehat{\boldsymbol{\theta}}$. To determine whether this is the case, our strategy is to seek an estimator of Asy.Var[$\hat{\boldsymbol{\beta}}_i$]. Here, a re-sampling approach, based on the general ideas of Krinsky and Robb (1986) is used to provide an appropriate approximation to the sampling variation of $\hat{\boldsymbol{\beta}}_i$.

The procedure involves six simple stages, which we set out below:

1. Estimate the model as described above. Under standard regularity conditions we have that $\widehat{\boldsymbol{\theta}} \sim N(\boldsymbol{\theta}, \boldsymbol{\Sigma})$, where $\boldsymbol{\Sigma}$ will be consistently estimated by usual methods of obtaining the covariance matrix form maximum likelihood estimates.

2. Construct $\widehat{\boldsymbol{\beta}}_{\boldsymbol{i}}$ as described in equation (8).

3. Take a random drawing of $\boldsymbol{\theta}^m$ from $N(\widehat{\boldsymbol{\theta}}, \widehat{\boldsymbol{\Sigma}})$.

4. On the basis of this draw of $\boldsymbol{\theta}^m$, evaluate a simulated $\widehat{\boldsymbol{\beta}}_i^{\boldsymbol{m}}$ using equation (8) replacing $\widehat{\boldsymbol{\theta}}$ with $\boldsymbol{\theta}^m$, *using the same draws of* $\mathbf{v}$ *as used in estimation.*

5. Repeat this process a large number of times (say $m = 1, \dots, M = 1{,}000$).

6. The empirical standard deviation of M different values for $\widehat{\boldsymbol{\beta}}_i^{\boldsymbol{m}}$ is then a valid estimate of the empirical standard error of $\widehat{\boldsymbol{\beta}}_i$, and moreover one that, unlike equation (9), explicitly takes into account the sampling variation of $\widehat{\boldsymbol{\theta}}$.

We now illustrate this technique with an application to the voting behavior of members of the Monetary Policy Committee (MPC) of the Bank of England.

4 Application: the voting behavior of the Bank of England's MPC

We use a panel dataset of Bank of England MPC members' votes for the period August 1997-December 2011. The panel contains data for 30 members and contains 1550 observations. Members' votes were classified into three categories: $y_{it} = -1$ (rate reduction); $y_{it} = 0$ (no-change); and $y_{it} = 1$ (rate increase) such that the ordered probit equation captures propensities to lower, leave unchanged, or raise the policy rate.[4] In terms of explanatory variables, we purposely restrict ourselves to a parsimonious specification to keep our analysis simple: votes are modeled as a function of the Bank's quarterly modal projections for inflation and output growth at the eight and four quarter horizons, respectively, modified as in Goodhart (2005), and expressed in terms of the deviation from the inflation target and an assumed 2.4% rate of potential output growth. We denote these variables $\pi_{Dev,t}$ and GAP_t, respectively, and note that such an approach closely follows previous contributions to the literature on MPC voting behavior, where members' votes are modeled using a Taylor-type rule.[5]

Two models were estimated: a simple pooled ordered probit model (OP); and a random parameters ordered probit, labeled RP-OP, in which random parameters were estimated across all MPC members for both $\pi_{Dev,t}$ and GAP_t. Our findings are presented in Table 1. We also take the step of recovering: (*i*) all of the member-specific random parameters estimated using expression (8); (*ii*) their associated *simulated standard errors* based on stages 1-6 outlined in Section 3; and (*iii*) *standard deviations* based on expression (9). This results of this exercise are given in Table 2.

Turing first to Table 1, the Akaike and Bayesian Information Criteria clearly identify the random parameters ordered probit (RP-OP) model as the preferred specification (as does a likelihood ratio test). As reflected by the estimates of σ_π^2 ,

[4] As votes to change the policy rate overwhelmingly occur in 25 basis point increments, this not only makes the data well suited for a discrete choice approach, but means that virtually no information is lost by using only three choice categories.
[5] See for instance Besley, Meads and Surico (2008), Harris and Spencer (2009) and Brooks, Harris and Spencer (2012).

σ^2_{GAP}, and their respective standard errors, there exists statistically significant variation in the estimated random parameters for these variables, indicating strong evidence of (unobserved) parameter heterogeneity. This result reinforces previous findings in the literature that MPC members have different interest rate reaction functions.[6] The extent to which parameter heterogeneity manifests itself is evident in Table 2, which gives the estimates of members' individual-specific parameters. As can be seen, the nature of the heterogeneity cuts through the institutional distinction between internally and externally appointed MPC members.[7]

Table 1: Estimation Results – All Models[a]

Variables	**OP**	**RP-OP**
$\pi_{Dev,t}$	0.1112***	0.3049***
	(0.01599)	(0.05454)
GAP_t	0.3851***	0.2802***
	(0.04023)	(0.1080)
μ_0	-1.083***	-1.177***
	(0.04023)	(0.1002)
μ_1	1.167***	1.277***
	(0.04463)	(0.1037)
σ^2_π	-	0.2779***
		(0.04780)
σ^2_{GAP}	-	0.4300***
		(0.1506)
AIC	2302.9633	2224.1090
BIC	2324.3163	2256.1384
CAIC	2328.3163	2262.1384
LogL	-1147.4817	-1106.0545

[a]Standard errors in parentheses
***/**/* Denotes two-tailed significance at one/five/ten percent levels

To enrich our understanding of these estimated parameter values, we also present estimates of their associated simulated standard errors and standard deviations, respectively denoted $\beta^i_{\pi_{Dev}}(sim)$ and $\beta^i_{\pi_{Dev}}(sd)$ for the inflation variable, and $\beta^i_{\mathrm{GAP}}(sim)$ and $\beta^i_{\mathrm{GAP}}(sd)$ for the output gap. A number of remarks can be made on the reported sets of estimates. Interestingly, the estimated values of the simulated standard errors are in all but one case *less* than the estimated standard deviations, and are typically two or three times smaller in absolute size. This phenomenon, we propose, has non-negligible implications should the econometrician wish to use these reported metrics to assess whether the recovered coefficients should be interpreted as being *statistically significant*. As a case in point, consider that the econometrician uses $\beta^i_{\pi_{Dev}}(sim)$ and $\beta^i_{\pi_{Dev}}(sd)$ to

6 For instance, in a neat paper, Gerlach-Kristen (2009) demonstrates that different interest-rate reaction functions are in turn attributable to MPC members having different loss functions.

7 In the MPC literature this broad distinction is sometimes used as a crude basis for introducing parameter heterogeneity, as in Harris and Spencer (2009). For an informative discussion of the differences between internal and external MPC members (alternatively referred to as *insiders* and *outsiders*, respectively), see Gerlach-Kristen (2003).

gauge the statistical significance of members' individual-specific recovered parameters for inflation, using a two-tailed test: at the one, five and ten per cent levels of statistical significance for the $\beta^{i}_{\pi_{Dev}}(sim)$ ($\beta^{i}_{\pi_{Dev}}(sd)$) measure, the number of statistically significant inflation parameters is, respectively, 25(17), 0(6) and 2(0). These differences are heightened for the output gap coefficients, where we observe that the number of statistically significant parameters is, respectively, 17(4), 3(4) and 1(5). In Table 2, asterisks are used to denote the varying levels of statistical significance associated with these different approaches to inferring significance. The choice of metric therefore has a clear impact on inference.

To bring this point home, and as an illustrative example, we consider the implications of the choice of metric for Mervyn King, who is notable for not only serving as a Governor of the Bank of England from 1st July 2003 to 30th June 2013, but for being present in all meetings in our sample.[8] Figure 1 plots the estimated probability of King leaving the interest rate unchanged for different sized deviations of forecast inflation from target (labelled 'beta') under a zero output gap assumption, which is achieved by setting $\mathrm{GAP}_t = 0$. The figure also plots the corresponding 95 per cent confidence intervals based on stimulated standard errors (red lines, labelled beta ± 1.96*sse) and standard deviations (blue lines, labelled beta ± 1.96*sd). We also note that for each measure, lines associated with the *lower bound* of a member's random parameter are dashed, whereas the *upper bound* is represented by unbroken lines. In this regard, Figure 1 shows that under the standard deviation measure the probability of King leaving the interest rate unchanged when $\pi_{Dev,t}$= 0.5 is in the range [0.393, 0.655]; in contrast, the *simulated standard errors* imply a markedly narrower range given by [0.509, 0.568]. The figure additionally demonstrates how greater (smaller) absolute coefficient values are associated with an increasingly smaller (larger) probability of voting to change the policy rate.

Although not the primary focus of this paper, we also note some interesting results with regards to the actual values of our estimated individual-specific parameters. *Prima facie*, their values can be interpreted as reflecting a clear regime shift in monetary policy for the period under scrutiny, which straddles the *pre*- and *post*-global financial crisis (GFC) periods. Here, it is noteworthy that prior to the onset of the GFC and in the short period following its climax in September 2008,[9] the Bank of England used the short-term interest rate ('Bank

[8] An academic economist, King joined the Bank in March 1991 as Chief Economist and Executive Director. Immediately prior to this he served as a non-executive director of the Bank. King was appointed *de facto* Deputy Governor in 1997, formally taking up this post on 1st June 1998 for a five-year term when the 1998 Bank of England Act came into force. After his second term as Governor (and therefore as Chairman of the MPC) ended on 30th June 2013 – a date which post-dates the end of our sample period – King was succeeded by Mark Carney.

[9] The GFC refers to a series of events beginning in the United States in latter part of 2007, which culminated in the collapse of Lehman Brothers in September 2008. Due to the global interconnectedness of financial markets and institutions, severe financial distress was experienced in many advanced industrialized countries other than the US, including the UK. The severity of the crisis caused many affected economies to experience significant falls in output, which led to central banks reducing short-term interest rates to near zero levels coupled with the introduction of 'unconventional' monetary policies, such as *quantitative easing*. For excellent accounts of the GFC, and its causes and consequences, see Mishkin (2011) and Mizen (2008).

Rate') as the main instrument of monetary policy. However, at its March 2009 meeting, the MPC reduced the Bank Rate to 0.5 per cent, a level deemed by its members to be the *nominal zero lower bound* (NZLB).[10] This action simultaneously coincided with the MPC's decision to adopt 'unconventional' policy measures in the form of *quantitative easing* (QE) via an asset purchasing facility, a decision taken primarily because at the NZLB, further reductions in the Bank Rate to stimulate the economy are no longer possible.[11]

In terms of the monetary policy strategy pursued by the MPC, a policy-regime shift associated with the introduction of QE is clearly observed, and is reflected in the votes of committee members. In our sample, the period March 2009 to December 2011 - *henceforth the* 'NZLB period'[12] - is characterized by the MPC voting to increase the level of asset purchases (predominantly gilts) whilst holding the Bank Rate at 0.5 percent. During this period the majority of MPC members *always* voted to leave the Bank Rate unchanged, behavior which is markedly different to that observed during the so-called 'Great Moderation' era[13], when members' individual votes are characterized by considerably more variation in response to changing (forecast) economic conditions.

Such behavioral differences are seemingly reflected in the RP estimates for members who are observed to spend the entirety of their time serving on the MPC during the NZLB period, and particularly those who *always* voted to maintain the Bank Rate at 0.5 percent. Table 2 identifies these members using a '♦': we observe that for instance, Paul Fisher, David Miles, Adam Posen, and Ben Broadbent all share random parameters on both inflation *and* output that are generally relatively negligible in size, statistically no different to the zero, or both.[14] Naturally, these findings do not mean that these members were unresponsive *per se* to changes in (forecast) economic conditions during our sample period; rather, these members can be viewed as adopting measures to stimulate the economy through continually voting to keeping the Bank Rate as low as possible – at 0.5 percent – whilst simultaneously voting to increase asset

[10] Put another way, the committee felt that for operational and technical reasons, it was not feasible to reduce the Bank Rate further.

[11] For an excellent discussion of quantitative easing and unconventional monetary policy, see Joyce, Miles, Scott and Vayanos (2012), and the accompanying collection of articles in the features edition of the *Economic Journal*, vol.122, issue 564.

[12] In the NZLB period, MPC members were required to vote on *two* policy proposals, relating to namely: (*i*) the value of asset purchases; and (*ii*) the level of the Bank Rate. Prior to this period members voted solely on the type of proposal given by (*ii*). In this paper, only votes on the short term interest rate are modelled.

[13] Clarida (2010) defines the 'Great Moderation' as being characterised by "predictable policy, low inflation, and modest business cycles", a period which for the UK began in the final quarter of 1992 (Benati, 2008). Based on our own calculations, this was followed by 61 quarters of uninterrupted positive output growth until the second quarter of 2008 - *the period immediately prior to the climax of the global financial crisis*. The first 10 years of our panel dataset (which begins in 1997) therefore encompasses a considerable part of this historically stable period.

[14] This finding is in broadly in keeping with Martin and Milas (2013), who find that the Taylor rule breaks down after 2007, due to the estimated response to inflation falling markedly and becoming insignificant.

purchases, something which is not modelled here.[15] Nevertheless, we consider this particular feature of the data as a useful 'validation' test with respect to the plausibility of our random parameters estimator: sizable and significant parameters over inflation and output for the aforementioned members would be considered implausible.[16]

For those MPC members who served the majority or all of their time during the 'Great Moderation' era, we typically observe that the inflation and output coefficients are positively signed, which is not unexpected:[17] given the ordered (trichotomous) nature of our model, positive coefficients imply a positive (negative) propensity to raise rates corresponding to a vote to increase (reduce) the interest rate. This view is in keeping with the idea that if the economy is overheating (characterized by our measure of forecast output being *above* potential), rates will be raised to dampen demand and bring inflation back to target; likewise, if forecast inflation is above target, then *ceteris paribus*, the response of the central bank will be to increase the short term interest rate to bring inflation back under control.

5 Conclusion

Post-estimation, researchers are often interested in individual-specific parameters. This paper adds to a growing strand of literature on random parameter estimation, which has been facilitated by increased computing power and the development of simulation based estimation techniques. Our main contribution has been to present an easily implementable method of correctly calculating the standard errors of random parameters, which explicitly takes into account the sampling variation of the estimated parameters of the model.

We illustrated the usefulness of such an approach through applying it to a panel data set based on MPC members' votes on the short-term interest rate. We envisage that this technique will be useful in a wide range of empirical applications, namely where the applied researcher is interested in drawing correct inference on the individual-specific random parameters of a model.

[15] Neuenkirch (2013) investigates how the MPC's voting record on the size of asset purchases during the NZLB period can be used to predict future asset purchases.

[16] It is notable here that three committee members who served either their full tenure, or the majority of it in the post-2008 period (Spencer Dale, Martin Weale, and Andrew Sentance) during the NZLB period in our sample voted on a number of occasions to raise the Bank Rate by either by 25 basis points or by 50 basis points, in addition to holding the Bank Rate at 0.5 per cent on other occasions. These members were often identified in the news and financial media as exhibiting 'hawkish' behaviour, a characterization which is reflected in their individual specific estimates on the output gap: all of these members display a preparedness to raise interest rates when forecast output growth is greater than its assumed potential.

[17] In the case of output, these parameters are observed not to be as statistically significant as those for inflation. This finding is in fact consistent with the findings of Besley *et al*. (2008) and Harris and Spencer (2009), who find that the output gap variable is not statistically significant.

Table 2: MPC members' random parameters over π_{Dev} and GAP_t with simulated standard errors and standard deviations

	π_{Dev}			GAP_t		
MPC Member	$\beta^i_{\pi_{Dev}}$	$\beta^i_{\pi_{Dev}}(sim)$	$\beta^i_{\pi_{Dev}}(sd)$	β^i_{GAP}	$\beta^i_{\text{GAP}}(sim)$	$\beta^i_{\text{GAP}}(sd)$
Mervyn King●	0.1546	0.00915***	0.04206***	0.3105	0.03001***	0.1332**
Eddie George●	0.4025	0.02518***	0.1132***	0.3998	0.05921***	0.2121*
Ian Plenderleith●	0.3611	0.02341***	0.1168***	0.3961	0.07056***	0.2229*
David Clementi●	0.4389	0.0294***	0.1157***	0.498	0.08025***	0.2221**
John Vickers●	0.7207	0.08973***	0.1781***	0.4763	0.1253***	0.2771*
Charles Bean●	0.1095	0.01181***	0.03997***	0.2936	0.05207***	0.155*
Paul Tucker●	0.0925	0.01151***	0.04369**	0.3896	0.05284***	0.1609**
Andrew Large●	0.5251	0.05512***	0.1495***	0.484	0.1302***	0.3249*
Rachel Lomax●	0.3319	0.0289***	0.1285***	0.2231	0.09065***	0.2956
John Gieve●	0.5632	0.05774***	0.1584***	0.2291	0.09129**	0.2703
Spencer Dale●	0.09048	0.00938***	0.0422**	0.3187	0.03931***	0.1847*
Paul Fisher●,♦	0.04212	0.01232***	0.04791	0.1038	0.07519	0.226
Willem Buiter●	0.8125	0.09678***	0.1474***	0.06846	0.1037	0.2169
Charles Goodhart●	0.67	0.07227***	0.1599***	0.09219	0.1005	0.2318
De Anne Julius●●	0.3232	0.04463***	0.148**	0.8442	0.1545***	0.236***
Alan Budd●●	0.6428	0.07966***	0.1951***	0.1123	0.102	0.2459
Sushil Wadhwani●●	0.5328	0.0378***	0.1306***	0.3797	0.0983***	0.3665
Stephen Nickell●●	0.6809	0.06739***	0.138***	-0.7333	0.3594**	0.252***
Chris Allsopp●●	0.5258	0.03906***	0.1319***	-0.3334	0.283	0.3305
Kate Barker●●	0.1656	0.01374***	0.05276***	0.2081	0.06009***	0.1784
Marian Bell●●	0.4362	0.05271***	0.1503***	-0.082	0.1804	0.33
Richard Lambert●●	0.3697	0.04001***	0.1507**	0.204	0.1089*	0.3346
David Walton●●	0.5466	0.1107***	0.2532**	0.3614	0.09393***	0.3687
David Blanchflower●●	0.05239	0.03028*	0.06137	0.8571	0.1681***	0.2301***
Timothy Besley●●	0.1217	0.00883***	0.05894**	0.2842	0.04904***	0.2285
Andrew Sentance●●	-0.03662	0.02166*	0.0356	0.9379	0.1403***	0.1694***
David Miles●●,♦	0.008048	0.01237	0.07031	0.08869	0.07854	0.2362
Adam Posen●●,♦	0.008376	0.01075	0.0698	0.1055	0.08403	0.2351
Martin Weale●●	0.07082	0.01316	0.07424	0.7475	0.189***	0.3305**
Ben Broadbent●●,♦	0.01629	0.01879	0.1167	0.1811	0.131	0.4182

***/**/* Denotes two-tailed significance at one/five/ten percent levels.
●/●● Denotes internal/external member;
♦ Denotes a member who served all of their time on the MPC during the NZLB period and always voted for a policy rate of 0.5%.

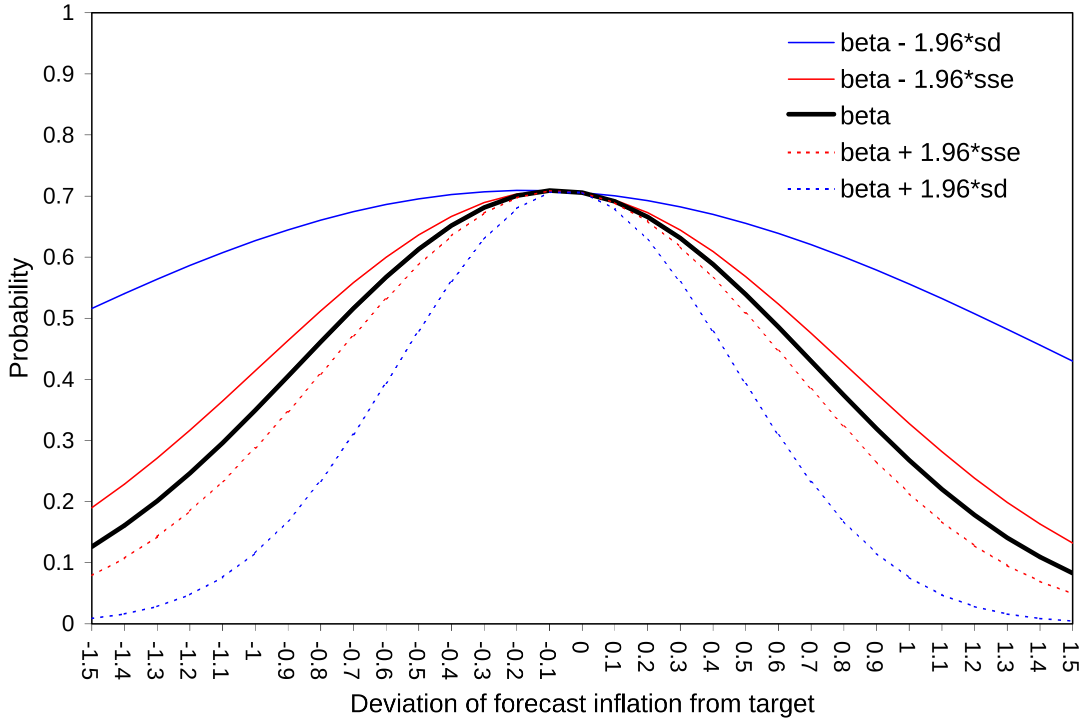

Figure 1: The probability of Mervyn King leaving the interest rate unchanged given deviations of forecast inflation from target under a zero output gap assumption, plotted with corresponding 95% confidence intervals based on stimulated standard errors and standard deviations.

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CONTACT

Bankwest Curtin Economics Centre
Curtin University
Kent Street Bentley WA 6102
GPO Box U1987 Perth WA 6845

Tel: +61 8 9266 2873

bankwesteconomicscentre@curtin.edu.au
business.curtin.edu.au/bcec

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CONTACT

Bankwest Curtin Economics Centre
Curtin University
Kent Street Bentley WA 6102
GPO Box U1987 Perth WA 6845

Tel: +61 8 9266 2873

bankwesteconomicscentre@curtin.edu.au
business.curtin.edu.au/bcec