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ABSTRACT

Optimal Sliding Scale Regulation: An Application to Regional Electricity Distribution in England and Wales*

This paper examines optimal price (i.e. 'sliding scale') regulation of a monopoly when efficiency and managerial effort are not observed. We show how to operationalize this model of incentive regulation and use actual data from electricity distribution in England and Wales to make welfare comparisons of sliding scale regulation with a price cap regime and the First-Best (the full information case). Our method enables us to quantify technical uncertainty as faced by the electricity regulator in the 1990s and shows that there are significant welfare gains from a sliding scale relative to the price cap regime.

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1 Introduction

The regulation debate has posed two polar price rules for an industry monopolist. Productive efficiency is achieved by price cap regulation, in which the firm is the residual claimant of cost-savings made within a period, and allocative efficiency is achieved by cost-plus regulation, which allows the firm to receive a specified rate of return by enabling the price to shadow costs. Both rules have been used at various times to set prices in regulated utilities, in a variety of countries. The development, and widespread application, of RPI-X price cap regulation in the UK is widely regarded as a significant innovation in regulatory practice (see Armstrong *et al.* (1994)). However, such mechanisms have not gone unchallenged, by policy-makers or academics. Government publications (see DTI (1999)) and regulatory price reviews in energy and water have all asked whether modifications to RPI-X would be appropriate (e.g. OFFER (1999a), OFFER (1999b)) in order to "incentivise regulation", as one commentator has suggested (see *Utilities Journal* (2000)). The recent review of electricity distribution price regulation (OFGEM (2004b)) contains several mechanisms to achieve this, within an overall RPI-X price cap framework. One of these, designed to cover distributors' costs of capital expenditure, resembles the incentive regulation studied in the present paper.

Any incentive scheme must address the principal-agent problem faced by the principal (the regulator). Optimal incentive schemes, designed to take account of information asymmetries, involve a *menu* of contracts that force the firm to surrender its private information (Laffont and Tirole (1993), Burns *et al.* (1998)).[1] These schemes can be regarded as 'sliding scale regulation' (profit-sharing—Burns *et al.* (1995)) because they allow higher cost firms

[1] See Jamasb *et al.* (2004) for interesting confirmation of the importance of asymmetric information and strategic behaviour in the context of electricity regulation.

to share more of this cost with consumers through a higher regulated price: they provide an intermediate point between the high-power incentives under price cap regulation and the low-power incentives of cost-plus regulation. Unfortunately, there has only been limited research on such schemes, perhaps because they may be complex to construct and necessarily hard to evaluate.[2] The purpose of this paper is to consider these two issues and, as a result, to compare optimal and simple forms of regulating an industry monopolist when efficiency and managerial effort are not observed.

In order to address the regulator's problem under asymmetric information, we draw upon Laffont and Tirole (1993). We amend this for the case of electricity distribution, then show how to operationalise their general model in order to construct a sliding scale form of regulation for electricity distribution (the context of the above-mentioned OFGEM proposal for a capital expenditure sliding scale) where contracts are offered linking the regulated price to observed costs.[3] Having shown how to construct the sliding scale, we seek to compare the welfare effects of such regulation with those of a price cap. We perform simulations where the key parameter values are estimated using demand and cost data from the distribution activities of the electricity supply industry in England and Wales. Because the industry was divided into twelve Regional Electricity Companies (RECs) upon restructuring in 1989, it provides a convenient panel for performing such analysis.[4]

[2]Anticipating the current paper, Laffont and Tirole (1993), p. 155, observe that: "...much work remains to be done, ..., it would be worthwhile to further analyze the properties of and to calibrate the optimal sliding scale ...".

[3]Burns *et al.* (1998) make a case for sliding scale regulation and compare this with alternative regimes. In constructing the latter they consider the simpler case where transfers take place between the regulator and the industry. By contrast, we consider price regulation in the absence of any such transfer.

[4]Although our data pre-date recent changes to the regional structure of electricity *supply* (see Green and McDaniel (1998)), our focus on regional monopolies in *distribution* (by what are now termed Distribution Network Operators, rather than RECs) remains

As a result, we are able to compute for each REC, a meaningful estimate of the welfare gain available from moving between a price cap and optimal (static) price regulation in distribution.[5] We find that, when the regulator designs both mechanisms to cover almost all possible distribution costs for a given REC, and when she faces a relatively severe asymmetric information problem, significant welfare gains may be available from the sliding scale.

Other authors have compared the welfare effects of different incentive schemes using simulation; see Gasmi *et al.* (2002). Schmalensee (1989) contrasts different linear mechanisms (where the regulated firm receives a fixed percentage cost-reimbursement). He uses sensitivity analysis with a selected range of parameter values. This approach is also adopted by Gasmi *et al.* (1994), where optimal regulation, price caps and a version of profit-sharing are compared in a model where the regulator is able to make lump-sum transfers to the firm. An important contribution of our work is to extend this analysis to optimal (linear) price regulation in the absence of such transfers. Of course, the practical merits of simulations are influenced by the plausibility of the parameter values used. Accordingly, Gasmi *et al.* (1997) calibrate a model of regulation in the US local exchange telecommunications market in order to examine empirically the form of the optimal regulatory mechanism. Using an engineering process model to estimate firms' (translog) cost functions, they look for evidence of natural monopoly and the degree to which regulatory mechanisms must be adjusted for firms' private information. Their paper is closely related to ours in its attempt to generate

highly relevant to current arrangements (see OFGEM (2000), OFGEM (2004b)). We continue to refer to 'RECs' to be consistent with our data.

[5]It should be made clear that our intention is not to test predictions from the model, or to supplement any of the body of empirical work seeking to evaluate the results of electricity privatisation (e.g. Newbery and Pollitt (1997), Green and McDaniel (1998), Newbery (1998), Wolfram (1998), Green (1999), Wolfram (1999)).

empirically meaningful values for the model's key parameters. Our approach and focus differ, however. Rather than use engineering data to construct a detailed cost function, we use economic data on costs, outputs and prices for RECs over time to estimate simplified cost and demand functions for each REC. This has the benefit of enabling us to estimate standard errors which proxy the regulator's degree of uncertainty about firms' cost functions, something that has not been done before. Then, having shown how to construct optimal linear price regulation without transfers, we use our empirical results to compare this with the welfare effects of a simple price cap.

The rest of this paper is organised as follows. Section 2 sets out the model we use before Section 3 solves the First-Best (benchmark) case where the firm possesses no private information. Section 4 derives the optimal price regime relating the regulated price to observed costs. We show how this scheme can be computed from a set of differential equations with initial and terminal boundary conditions. Section 5 derives the price cap regime. Section 6 then explains how we estimate the parameters necessary for the welfare comparison of the distribution price cap and sliding scale for the electricity industry in England and Wales, before presenting the results of our simulations. The final section (Section 7) concludes and highlights several aspects of the analysis that warrant future research.

2 A model of price regulation in electricity distribution

Our paper seeks to examine the general question of how optimal price regulation compares with price cap regulation in the presence of asymmetric information. Given that the data we use in Section 5 are drawn from electricity distribution, it is important that our model reflects this setting.

Production of electricity typically consists of four functions: generation, transmission, distribution and supply. The economic characteristics of these functions mean that some can be opened up to competition more readily than others. In England and Wales, generation and supply have gradually become more competitive since restructuring in 1989 and privatisation in 1990, while transmission and distribution have remained subject to price regulation. Since we examine optimal price regulation based on Laffont and Tirole (1993)'s model of consumer price regulation, we must first consider whether any amendments are necessary when regulating an upstream component of consumer price.

To this end, note that the electricity retail price (p) is primarily the sum of the contributions of the four components described above, generation (g), transmission (t), distribution (d) and supply (s): i.e. $p = g + t + d + s$.[6] The issues for us are then whether a relationship between p and d can be expected to exist and how it might be modelled. On the first point, it is clear from OFGEM (2004b) (e.g. see the Summary) that the regulator recognizes a positive relationship between d and p and that we should therefore include this. On the second point, it is again apparent from OFGEM (2004b) that, with the exception of pass-through for certain upstream costs, much of the regulator's analysis takes the other sectors' prices and costs as given when setting distribution prices. We shall, thus, make a similar assumption: letting $z \equiv g + t + s$, we assume that z is taken as exogenous in the setting of d. As a result, if q is the final output and $p = P(q)$ be the inverse retail demand curve, we can write $d(q) = P(q) - z$.[7]

[6]These four elements account for 91% of p; see OFGEM (2004a), Figure 4.2.

[7]Future research might interestingly consider the effects of relaxing this partial equilibrium approach to take into account interactions between the four principal components

Consider the regulation of a regional natural monopolist in electricity distribution, supplying q units of electricity for sale on the downstream retail market. The retail price is a uniform (linear) price $p = d + z$, and the demand curve is $q = D(p) = D(d + z)$; the inverse demand curve is as above $p = P(q) \Leftrightarrow d(q) = P(q) - z$.[8] Total distribution costs, consisting of fixed and variable costs, are separately observed by the regulator and given by

$$C(e, q) = \alpha + c(e, q; \beta) \tag{1}$$

where e is cost-reducing effort ($C_e < 0$), q is output, α are fixed costs and β is a productivity parameter reflecting factors exogenous to the distributor that affect costs ($C_q > 0, C_\beta > 0$). In principle, β may be stochastic and change over time. Importantly, however, we assume that the firm observes the realisation of β before taking any decisions for the given period. Of course, the firm also knows e. In contrast, neither effort nor the productivity parameter are observed by the regulator, who faces both an adverse selection and moral hazard problem.[9] The regulator does, however, observe final costs

of price. For the present paper, however, our assumption provides a tractable starting point for modelling distribution price regulation. As we have suggested, it also finds some support in recent regulation.

[8]Throughout, we consider only linear pricing. See Wilson (1993) for analysis of non-linear alternatives.

[9]To give some specific examples, the electricity regulator may not be able to distinguish high costs caused by difficult (perhaps stochastic) distribution conditions (OFGEM (2004b), para. 3.18, contrasts “known” and “unknown” items of cost) or by poor managerial effort. Elsewhere, the rail regulator may not be able to tell if high costs genuinely result from “leaves on the line” for a particular train operating company (TOC). The firms, in contrast may well know what has influenced their costs. Of course, correlation across distributors or TOCs may provide useful information here (and allow some element of benchmarking) but we ignore this by assuming the βs to be independently distributed across firms. We recognise that the modelling of interdependence remains important future work. Laffont and Tirole (1993) examine interdependence in a model with lump-sum transfers rather than price regulation, while Auriol and Laffont (1993) do so in a model with no cost-reducing effort.

(C) and knows that β is continuously distributed on the interval $[\underline{\beta}, \overline{\beta}]$ with density function $f(\beta)$.

Single-period payoffs for the firm and regulator are

$$U(e,q) = R(q) - C(e,q) - \psi(e) \tag{2}$$

$$W(e,q) = B(q) - R(q) + U \tag{3}$$

In (2), $\psi(e)$ is the disutility of effort to the firm (where we assume $\psi', \psi'' > 0$ for $e > 0$ and $\psi(e) = 0$ otherwise). In (3), $B(q)$ is the gross consumer surplus from consuming the REC's electricity, $R(q) = pq$ is the revenue and $B(q) - R(q)$ is the net consumer surplus.

2.1 The First-Best (complete information)

A useful benchmark for later results is provided by assuming that the regulator has complete information. This 'First-Best' can be reached when the regulator observes the productivity parameter β. Then she maximizes (3) with respect to q and e, given the individual rationality (IR) constraint $U \geq 0$. The well-known solution (see Appendix A) involves optimal effort when the marginal disutility of effort equals its marginal benefit ($\psi'(e) = q$), Ramsey distribution pricing and zero rent (i.e. IR binds).

3 Incomplete information and sliding scale regulation

Now assume that neither the REC's efficiency β nor effort e can be observed by the regulator but price, demand, marginal and fixed costs are observed.[10] Let $\rho = U + \psi(e)$ be the total transfer received by the firm via the consumer. Then from the definition of U we can write

$$(d + z)D(d + z) - \alpha = \rho = U + \psi(e) \tag{4}$$

and let $d(C_q, \rho, \alpha)$ be the lowest distribution price satisfying this equation, where $C_q = \partial C/\partial q$ is the marginal distribution cost. Write the net consumer surplus as $B^n(d(C_q, \rho, \alpha) + z)$. The regulator now designs a menu $\{d(\beta), C_q(\beta)\}$ to maximize the expected welfare

$$\int_{\underline{\beta}}^{\overline{\beta}} [B^n(p(C_q(\beta) + z, \rho(\beta), \alpha) + U(\beta)] f(\beta)\, d\beta \tag{5}$$

where $\rho = U + \psi(e)$, subject to incentive compatibility constraints (IC) and IR constraints for each firm[11]:

$$IC: \quad \dot{U}(\beta) = -\psi'(e(\beta))\,; \;\; C_{q\beta} \geq 0 \tag{6}$$

$$IR: \quad U(\overline{\beta}) \geq 0 \tag{7}$$

[10] Assuming that other parameters (e.g. γ, η from Section 3.1 below) are the firm's private information would add significantly to complexity without necessarily altering our main qualitative results (see Laffont *et al.* (1987)).

[11] The IC constraint is the familiar one derived in Laffont and Tirole (1993) and describes each type of firm's first- and second-order conditions for truth-telling: effectively, rent must be allowed to evolve at the same rate as a low-cost firm loses utility from foregoing its chance to mimic high-cost counterparts. Since IC requires $\dot{U}(\beta) < 0$, we can infer that when $\overline{\beta}$'s IR constraint is satisfied, so are all other firms'. This is captured in (7).

The result of this optimization is obtained by standard optimal control techniques (see Laffont and Tirole (1993), p. 152) and is given by

$$\psi'(e(\beta)) = q(\beta) - \frac{\int_{\underline{\beta}}^{\beta} [\partial d/\partial C_q - 1] f(\tilde{\beta})\, d\tilde{\beta}}{(\partial d/\partial C_q) f(\beta)} \psi''(e(\beta)) \tag{8}$$

and $U(\overline{\beta}) = 0$. From the latter and the IC constraint (6) it follows that

$$U(\beta) = \int_{\beta}^{\overline{\beta}} \psi'(e(\tilde{\beta}))\, d\tilde{\beta} \tag{9}$$

Then price and output follow from the firm's budget constraint (4) and $q = D(d + z)$. Effort under asymmetric information is less than that under the First-Best (compare (8) and (A.2) from Appendix A).

3.1 Implementation of the sliding scale

The relationship $d = p - z$, equations (4), (8), (9), $\rho = U + \psi(e)$, $C_q = C_q(e, q; \beta)$ and $q = D(p)$ give seven equations in $p(\beta), e(\beta), U(\beta)$, $\rho(\beta)$, $C_q(\beta)$ and $q(\beta)$ given functional forms $D(\cdot), \psi(\cdot)$ and $f(\cdot)$. In fact given $\{d(\beta), C_q(\beta)\}$ the rest of the solution is uniquely defined. It follows that a contract consisting of a cost-contingent menu $\{d(\beta), C_q(\beta)\}$ implements the optimal solution. The IC constraint ensures that the firm with efficiency β chooses the correct contract designed for its type. Expressing the price as a function of cost for each β gives the *sliding scale* $d = d(C_q)$. An example of this solution is given in Figures 1a and 1b (discussed further below). For a very inefficient firm a reduction in cost is matched by an almost one-for-one reduction in price. For a very efficient firm the scheme almost resembles a price cap.[12]

Our system of equations as it stands contains two integral equations which are not straightforward to solve, even numerically. However we can transform the system into six first-order differential equations in $e(\beta)$, $U(\beta)$, $p(\beta)$, $k(\beta)$, $f(\beta)$ and $W(\beta)$, where $k(\beta)$ is defined in (11) below. These are amenable to numerical solution techniques so we proceed to do this.

On the demand-side, we specify $D(p) = Ap^{-\eta}$, where A represents the 'scale' (including income effects) of demand and $\eta > 0$ is the (absolute value of) the price elasticity of demand. On the supply-side, we specify $c(e, q; \beta) = (\beta - e)q \equiv \hat{c}q$, $\psi(e) = \frac{1}{2}\gamma e^2$, and

$$f(\beta) = \frac{1}{\sqrt{2\pi}\sigma} \exp -\frac{1}{2}\left(\frac{\beta - \mu}{\sigma}\right)^2 \tag{10}$$

i.e. a normal distribution with mean μ and standard deviation σ. Clearly, our simulations in Section 5 depend on the empirical validity of these assumptions. The constant elasticity demand function is standard in energy demand estimation (e.g. Pesaran *et al.* (1998)).[13] We check for the normality of the β-distribution when we estimate the cost function in Section 5. The remaining assumptions are addressed first in Appendix B, where we show how a more general disutility of effort function and a cost function that is non-linear in effort generate a cost function that is non-linear in output. Section 5 then tests this against our chosen cost function. Both here, and in the case of $f(\beta)$, our data are consistent with the above functional forms.

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[12]If β is stochastic but observed by the firm before choosing its $\{p, C_q\}$ combination (as described above), then the sliding scale allows firms to react to the realisations of β they actually observe.

[13]This specification is typically favoured for its simplicity, straightforward interpretation and limited data requirements. Moreover, Pesaran *et al.* (1998) find that it generally outperforms more complex specifications across a large variety of settings.

We begin by differentiating (4) to give

$$\frac{\partial p}{\partial \hat{c}} = \frac{D(p)}{D(p) + (p - \hat{c})D'(p)} \equiv k(\beta) \tag{11}$$

We can now rewrite (8) and (9) as

$$e = \frac{D(p)}{\gamma} - \frac{\int_{\underline{\beta}}^{\beta} [k(\tilde{\beta}) - 1] f(\tilde{\beta})\, d\tilde{\beta}}{k(\beta)} \tag{12}$$

$$U(\beta) = \gamma \int_{\beta}^{\overline{\beta}} e(\tilde{\beta})\, d\tilde{\beta} \tag{13}$$

and then differentiate (12) with respect to β to arrive at

$$\frac{de}{d\beta} = \frac{D'(p)}{\gamma}\frac{dp}{d\beta} + \frac{[D(p)/\gamma - e]}{k(\beta)f(\beta)}\left[fk\frac{df}{d\beta} + f\frac{dk}{d\beta}\right] - \frac{(k(\beta) - 1)}{k(\beta)} \tag{14}$$

and

$$\frac{dU}{d\beta} = -\gamma e \tag{15}$$

which returns us to the original IC condition. Differentiating (4), (11) and $\hat{c} = \beta - e$ we have

$$\left(\frac{dp}{d\beta} - \frac{d\hat{c}}{d\beta}\right) D(p) + (p - \hat{c})D'(p)\frac{dp}{d\beta} = \frac{dU}{d\beta} + \gamma e\frac{de}{d\beta} \tag{16}$$

Substituting $D(p) = Ap^{-\eta}$, $D'(p) = -\eta D(p)/p$, $k(\beta)$ defined in (11) becomes

$$k = \frac{p}{p(1 - \eta) + \eta\hat{c}} \tag{17}$$

Hence differentiating and putting $\frac{d\hat{c}}{d\beta} = 1 - \frac{de}{d\beta}$ we arrive at

$$\frac{dk}{d\beta} = -\frac{\eta}{[(1 - \eta)p + \eta c]^2}\left[p\left(1 - \frac{de}{d\beta}\right) - \hat{c}\frac{dp}{d\beta}\right] \tag{18}$$

Then differentiating (10) we have:

$$\frac{df}{d\beta} = -\frac{(\beta - \mu) f}{\sigma^2} \tag{19}$$

Social welfare can be incorporated within the system of differential equations as follows. With a demand function given by $D(p) = Ap^{-\eta}$ the net consumer surplus is given by

$$B^n(p) = B(q) - R(q) = \int_p^\infty D(p')\,dp' = \frac{A}{1-\eta}\left[(p^{max})^{1-\eta} - p^{1-\eta}\right] \tag{20}$$

Note that if $\eta < 1$, which turns out to be the case for the majority of our empirical results, the net consumer surplus is only defined if we impose a price ceiling. However we can subtract the troublesome constant first term in (20) from our definition of net consumer surplus without changing the relative welfare performance of the regimes. In what follows we report welfare with net consumer surplus defined as

$$B^n(p) = -\frac{A}{1-\eta} p^{1-\eta} = -\frac{pq}{1-\eta} \tag{21}$$

To calculate the expected welfare define

$$W(\beta) = \int_{\underline{\beta}}^{\beta} [B^n(p(\tilde{\beta})) + U(\tilde{\beta})] f(\tilde{\beta})\,d\tilde{\beta} \tag{22}$$

Then differentiating with respect to β we have

$$\frac{dW}{d\beta} = [B^n(p(\beta)) + U(\beta)] f(\beta) \tag{23}$$

which, using (20), can be added to the system of differential equations. Note the additional boundary condition $W(\underline{\beta}) = 0$. Define the row vector $v^T =$

$[e\,U\,p\,k\,f\,W]$. Then (14), (15), (16), (18), (19) and (23) can be written as the following system of non-linear first-order ordinary differential equations:

$$Z(v)\frac{dv}{d\beta} = B(v)\,; \quad \beta \in [\underline{\beta}, \overline{\beta}] \tag{24}$$

The relationship for the distribution price, $d(\beta) = p(\beta) - z$ then completes the set of equations for the sliding scale.

The boundary conditions are at both ends of the interval $[\underline{\beta}, \overline{\beta}]$. At $\beta = \underline{\beta}$ we have from (12) that $\underline{e} = D(\underline{p})/\gamma$ (i.e. effort is at the socially optimal level for the efficient firm). At $\beta = \overline{\beta}$ we have $U(\overline{\beta}) = 0$. We solve this problem numerically using MATLAB.[14] Before presenting our results, however, we first obtain an appropriate version of price cap regulation with which to compare the sliding scale.

4 Price cap regulation

We wish to compare the optimal scheme described above with an example of price cap regulation. Thus, we now explain how the price cap is chosen. Such regulation has been practiced in most regulated utilities in the UK since their privatisation although a number of variations have been added to the simple scheme we model.[15]

The stylised price cap regime is obtained as follows. A single price is set that will satisfy the IR condition for all firms. This means setting the price

[14] See Appendix C; the full programs are available from the authors on request.

[15] Our approach to modelling the price cap is similar to that in Gasmi *et al.* (1994). A scheme like RPI-X price capping has several additional features. These include the choice of X-factors (Bernstein and Sappington (1999), Bernstein and Sappington (2000)), various cost-passthrough dispensations that regulators may allow, matters of tariff rebalancing that might take place in a multi-product monopoly (Armstrong *et al.* (1995)) and intertemporal issues (Dobbs (2004).

at $\overline{p}$ to ensure $\overline{U} = 0$. Then, given the price, each firm will choose the optimal level of effort. Given (2) and our assumptions about $c(e, q; \beta)$ and $\psi(e)$, it is clear that when the price cap binds the distribution and retail prices, output, effort and cost are given by

$$\begin{aligned} \overline{d} &= \overline{p} - z \\ (\overline{p} - \overline{\hat{c}})D(\overline{p}) - \alpha &= \frac{\gamma \overline{e}^2}{2} \\ \overline{q} &= D(\overline{p}) \\ \overline{e} &= D(\overline{p})/\gamma \\ \overline{\hat{c}} &= \overline{\beta} - \overline{e} \end{aligned}$$

Note that, unlike the sliding scale, the price cap provides incentives for First-Best effort. As efficiency rises, the price arrives at the monopoly price for that level of efficiency and then the firm acts as an unregulated monopoly for higher efficiency (see Laffont and Tirole (1993), p. 154).

5 Estimation and simulation

Having characterised the optimal form of static price regulation and a simple price cap, we now wish to compare the welfare effects of the two using simulations. Because results here depend on the choice of parameter values, we attempt to estimate the parameters of interest from demand and cost data taken from electricity distribution in England and Wales. This allows our simulations to use suitable parameter values for the industry in question and enables us to estimate the degree of technological uncertainty (β) faced by the regulator. We first explain our approach to estimating the demand- and supply-sides of the model.

5.1 Method

On the supply-side of the model, we observe variable and fixed costs (α_i) separately for each REC i. From Section 4, variable distribution costs are given by

$$V_i = (\beta_i - e_i)q_i \tag{25}$$

Effort is not observed, so an assumption about its derivation is needed. We therefore assume that the actual regime currently in place approximates to a price cap, i.e. RPI-X regulation. Then effort chosen by rent-maximising REC i is given by $e_i = q_i/\gamma$. Substituting into (25), and allowing for variation over time, the following cross-sectional equation for average variable costs in REC i at time τ is obtained:

$$\frac{V_{i\tau}}{q_{i\tau}} = \beta_{i\tau} - \frac{q_{i\tau}}{\gamma} \tag{26}$$

Now put

$$\beta_{i\tau} = b_i + u_{i\tau} \tag{27}$$

where the zero-mean disturbance in (27), $u_{i\tau}$, is a REC-specific shock to β_i at time τ (observed by the REC).

For the demand-side, the relationship $q = D(d+z)$ is estimated. Suppose that we have the estimated long-run demand relationship in log-linear form: $\log(q_i) = a_i - \eta_i \log(p_i)$ where a_i may contain other variables, but these are exogenous from the viewpoint of the industry regulator. Putting $A_i = e^{a_i}$, we can then write

$$q_i = D(p_i) = A_i p_i^{-\eta_i} \tag{28}$$

for the ith REC. Here, q_i represents total electricity demand for REC i and η_i is the absolute value of the long-run price elasticity of demand for this

REC. Notice that since A_i and η_i are different for each REC we construct a different sliding scale for each REC.

5.2 Estimation results

5.2.1 Estimation of average variable costs

Equations (26) and (27) represent a static fixed effects model of average variable costs to be estimated for electricity distribution in England and Wales. Let $y_i = V_i/q_i$, $\xi = -(1/\gamma)$. Then (26) can be rewritten as

$$y_{i\tau} = b_i + \xi q_{i\tau} + u_{i\tau} \tag{29}$$

This can be estimated by least squares dummy variables.[16,17] The data set covers the period 1990/01 to 1999/2000 and thus, spans the period since privatisation. Full details about the data are given in Appendix D.

Over the historic period many other factors are likely to have impacted on average operating costs including the severity of the regulatory regime, ownership changes amongst the RECs, changes in environmental legislation, and so on. Failure to include these may produce biased estimates of the desired coefficients. This problem is primarily dealt with by use of group

[16]We assume that $E(q_{i\tau}, u_{i\tau}) = 0$, for unbiasedness when estimating (29). Since shocks to $q_{i\tau}$ must come from the demand-side of the model, and since we interpret $u_{i\tau}$ as a supply-side shock, unbiasedness would arise from demand and supply shocks being uncorrelated. In general, this seems reasonable. Another potential source of bias could be output measurement error. To the extent that our output data are collected to satisfy regulatory, as well as private, requirements (see Appendix D), we feel that scrutiny of measured/reported figures will have helped to address this.

[17]Our procedure estimates a confidence interval for γ, while we have assumed the regulator knows γ with certainty in the model (the same is true for η below). This suggests that the procedure would be appropriate for a more complex setting where, say, γ is also private information. However, to the extent that a more complex setting need not qualitatively alter our results (see n. 10), we believe our estimating procedure remains valid.

effects (i.e. dummy constants for each REC) plus an allowance for time effects. Two approaches are considered: time dummy variables and a time trend. In addition, in order to check the (derived) linearity of (29), both approaches test for the presence of a squared term in output (q^2). The general model is therefore:

$$y_{i\tau} = b_i + \xi q_{i\tau} + \kappa q_{i\tau}^2 + \text{REC effects} + \text{time effects} + u_{i\tau} \qquad (30)$$

where 'time effects' are either time dummies *or* a time trend.

The results for the general model with time dummies are presented as specification C1 in Table 1. The coefficient for q has the expected sign and is significant at the 5% level. The coefficient for q^2 also has the expected sign but is insignificant at standard significance levels. In addition, the equation fails the two diagnostic tests for functional form (RESET) and normality. The results from removing the q^2 variable are presented as specification C2 in Table 1. As expected the coefficient on q falls but remains significant at the 1% level and the normality test is now passed at the 5% level. However, the RESET test is still not passed at conventional levels of significance.

The results for the general model with the time trend are presented as specification C3 in Table 1. Again the coefficient on q has the expected sign and is significant at the 5% level. The coefficient for q^2 also has the expected sign and is significant at the 10% level. The time trend is not significant at conventional levels. For this equation the functional form test is passed at the 5% level, but there is evidence of non-normality. When the q^2 term is removed—specification C4 in Table 1—both the RESET and the normality tests are passed at the 5% level. In addition the q coefficient remains very significant with the expected sign, while the time trend, although negative as expected, is very insignificant. Overall, this specification ensures that the important diagnostic tests for our specification of (1), $\psi(e)$ and $f(\beta)$ are passed. Accordingly, it is the one used in the simulations below.

Table 1 about here

The final step is to calculate the range of uncertainty faced by the regulator when seeking to assess each REC's cost; this is something that our estimation approach allows us to consider. Equation (26) takes the value of γ as fixed so we focus on the uncertainty surrounding the β_is. These are found from the standard error estimates of the REC effects in model C4 and are presented in columns (3)–(6) of Table 3 at the end of this section; these present the range of uncertainty for 95% and 99% confidence intervals (Ranges 1 and 2 respectively). These can be used to construct upper and lower bounds for each β_i. Thus, in the case of REC 1 for example, the regulator can estimate β_1 to be 2.58. However, with 95% confidence this will fall between 2.00 (a shock that lowers the REC's costs) and 3.17 (implying an adverse shock to costs). Naturally, the 99% confidence intervals take account of even greater potential shocks to costs.

5.2.2 Estimation of electricity demand

Estimation of (28) requires specification of the exogenous variables that are likely to have affected regional electricity demand in England and Wales. One approach would be to estimate a separate demand function for each company, but this would require a lengthy time-series for each of the required variables. Instead, we exploit a panel of data on regional electricity demand. The panel covers all twelve RECs for the period 1982/83 to 1996/97. We run the following long run panel model:

$$\log q_{i\tau} = a_i + (\omega + \delta_i) \log p_{i\tau} + \sigma \log h_{i\tau} + \zeta \log q_{i\tau-1} + \text{REC effects} + \text{time effects}$$

where $\log q_{i\tau}$ is the logarithm of electricity demand for each REC, $\log p_{i\tau}$ is the logarithm of the real price of electricity, and $\log h_{i\tau}$ is the logarithm of real GDP in region i at time τ.[18] As with the cost function, two ways of incorporating the time effects were initially considered: either time dummies or a time trend. In addition, given the longer time series available for the demand estimation a lagged dependent variable was included. The estimated coefficients are given in Table 2 and the implied long run elasticities are reported in Table 3 (column 8).

Table 2 about here

Specification D1 incorporates time dummies whereas specification D2 incorporates the time trend. The results for D2 are poor, failing the serial correlation and the functional form (RESET) tests. Moreover, the price elasticity estimates are poorly defined. Therefore the model with a time trend is not considered further. However, for specification D1 the price elasticities are generally well defined, other than that for REC 8 where the coefficient on $\log p_8$ is positive but very insignificant. In addition, specification D1 passes the serial correlation and RESET tests, but there are some problems with non-normality. Therefore, a number of outliers were identified and dummy variables included in the model, with the results presented as specification D3

[18] A more general model allowing for a different income elasticity of demand for each REC could have been employed. However, given the nature of the simulation exercise and the limited number of observations a constant income elasticity across all RECs was assumed.

in Table 2. The inclusion of the dummies solves the non-normality problem with all other diagnostic tests passed. Again the price elasticities are generally well defined other than that for REC 8. Thus, to ensure $\eta > 0$ in this case, the long run price elasticity for REC 8 was constrained to -0.05 and the results presented as specification D4 in Table 2. This passes all diagnostic tests, with the test for the imposed negative price elasticity accepted by the data. Moreover, all coefficients are significant at the 5% level other than the price coefficient for REC 10, which is significant at 14% only. In addition specification D4 has sensible income and price elasticity estimates with the long-run price elasticities ranging from -0.05 for REC 8 to -1.15 for REC 12. Therefore the coefficients from specification D4 are used below. A summary of all the parameter values needed for our simulations is given in Table 3.

Table 3 about here

5.3 Simulation results

We have performed simulations and welfare comparisons for each REC (Table 4). However, it is useful to begin by considering a given REC in more detail. Thus, Figures 1 and 2 display results for a representative REC (REC 1); similar figures and discussion can be provided for all the RECs. As described above, we design a sliding scale for two possible ranges of β: a 'narrow' range, where β is assumed to lie within a 95% confidence interval of the estimated value (i.e. Range 1), and a 'wide' range, where β is assumed to lie within a 99% confidence interval of its estimated value (i.e. Range 2), thereby capturing 99 percent of the possible values of β. These ranges represent the regulator's uncertainty as to the true value of β. We compare the sliding scale, price cap and First-Best regimes.

To begin, Figures 1a (Range 1) and 1b (Range 2) depict the sliding scale computed for REC 1. As explained earlier, this is increasing in the REC's marginal cost and ranges from a virtual price cap to almost complete cost-reimbursement as this cost increases. As a result, depending on its observation of β, the REC can select a price-cost combination from the menu offered. In terms of the prices offered on the two scales, there is little difference. As is common in these models, the convexity of the sliding scale means that it can be approximated by a menu of linear contracts linking final price to an agreed share of marginal cost to be borne by the firm.

Despite the sliding scale rising as conditions render the REC less cost-efficient, Figures 2a and 2b demonstrate that the overall transfer ($\rho = U + \psi(e)$) from consumers to the firm, still falls as β rises. This is further confirmed in Figures 3a and 3b which depict, *inter alia*, rent and cost-reducing effort under the sliding scale regime. In both cases, rent falls as β rises (as required by IC), with effort also falling in order for the regulator to extract rent from the more efficient of the potential RECs.[19]

Figures 3a and 3b also contain important information relevant to the welfare comparison between the sliding scale and the alternative regimes we consider: price caps and First-Best (full-information) pricing. Thus, while rent under the latter scheme is clearly zero, we can see that it is higher under price caps than either of the others. The reason for this is that the price cap makes no adjustment to efforts in order to extract rent from RECs if the REC experiences a low realisation of β: the REC is a residual claimant of any cost savings. These figures also confirm (as we have already seen) that effort will be higher under both First-Best and the price cap compared to

[19]Lower effort from high-β RECs means that low-β firms who mimic need to be reimbursed for smaller levels of disutility of effort.

the sliding scale; i.e. *ceteris paribus* firms will work harder to push down costs than under the sliding scale. Under the price cap, this again reflects the added incentive to cut costs.

Our final figures (4a and 4b) compare consumer prices under the three regimes. Naturally, First-Best prices are lowest (and increase with β), reflecting the regulator's ability to force down observable costs and match prices to them. Similarly, the price under the price cap is highest, in order to cover the REC's highest expected cost (within the relevant β-range). The sliding-scale prices lie between the two, again reflecting the regulator's desire to trade rent for cost-reducing incentives.

Figures 4a and 4b also provide the clearest observable differences between the two β-ranges we examine. Clearly the First-Best price does not change as the range does (for common values of β), while the price cap rises as the regulator tries to cover greater potential costs by moving to a 99% confidence interval. Although, as we saw in Figures 1a and 2a, the sliding scale does not alter much across the ranges, it moves relatively closer to First-Best pricing as the β-range widens, because of the ensuing increase in the price cap.

It is useful to quantify the welfare effects of the changes described above. To this end, we examine the benefits of sliding scale versus the price cap in terms of the following measure:

$$G = \frac{wel(ss) - wel(pc)}{wel(fb) - wel(pc)} \tag{31}$$

where $wel(i), i = ss, pc, fb$ is the social welfare under the sliding scale, price cap and First-Best regimes respectively. Thus, since $wel(fb) > wel(ss) > wel(pc)$, $G \in (0, 1)$. G is a measure of how much better the sliding scale regime is in relation to the price cap in solving the asymmetric information problem. Our results for all twelve RECs are contained in Table 4. For each range, it is apparent that the welfare gains from the sliding scale vary somewhat, although the average gains are appreciable. Thus, given asymmetric information, the Range 1 sliding scale makes up roughly 30 percent (on average) of the welfare loss under the price cap. As anticipated above, this improvement increases (to around 50 percent on average) as we move to the wider Range 2: when the regulator seeks to cover more efficiency levels, the price cap rises and the sliding scale's performance improves. An implication of this is that smaller benefits will accrue to the sliding scale if the regulator designs policy for only a narrow range of possible efficiencies. As explained above, the welfare gain comes about because the sliding scale allows the regulator to trade rent and efficiency in a way that the price cap prevents. When comparing the values of G across RECs, it is notable that the smallest gains tend to be associated with small standard errors in the estimation of β (e.g. RECs 6, 10 and 11). This is because small standard errors imply that the regulator's asymmetric information problem is relatively less severe, so the sliding scale has less 'work' to do.

Table 4 about here

6 Conclusions

We have shown how a sliding scale regulation scheme linking the regulated price to observed marginal cost can be constructed. Data from the twelve UK RECs (as they were called during our data period) have been used to estimate the parameters needed to simulate this scheme and to support the functional forms used to implement it. Unlike previous attempts to calibrate optimal regulatory mechanisms, the use of panel estimation allows us to gain some measure of the degree of technological uncertainty facing the regulator when seeking to ascertain firms' costs. Comparisons with a price cap regime for electricity distribution in England and Wales suggest that significant welfare gains are obtainable (as also confirmed by Gasmi *et al.* (1994)), especially when the regulator designs both schemes for almost every conceivable realisation of the unobserved productivity parameter and faces high uncertainty as to the regulated firm's costs.[20]

Our results are significant in the light of the UK debate surrounding price regulation and the provision of incentives in the utilities, including the focus of our study: the electricity industry. As various consultations regarding electricity distribution price reviews make clear (OFFER (1999a), OFFER (1999b), OFGEM (2004b)), regulators acknowledge facing notable information asymmetries when setting prices and, recently, the electricity regulator has proposed a sliding scale to cover the costs of distributors' capital expenditure (while retaining an overall RPI-X price cap). Given the strengths that we (and others) have found in optimal price regulation, such developments appear to have merit; it will be interesting to examine the effects of this proposal as it is rolled out.

There are several ways in which our paper would be extended. Some might be expected to weaken our results while others may strengthen them. Two complications in the former category are dynamic interaction between the regulator and the firm, and the challenges raised by regulating conglomerate utilities. Whilst acknowledging the superiority of sliding scale regulation in a static single-product context such as ours, Mayer and Vickers (1996) argue that relaxing these assumptions would favour price capping. The reasons for this are that cost-sharing dampens cost-reducing incentives so that, in or-

[20]In a sense, we have underestimated the gains from incentive contracts; increasing the space of characteristics unknown to the principal would be expected to increase these welfare gains.

der to achieve the efficiencies available under price capping, the regulatory lag would have to be lengthened which may in turn increase the regulator's time inconsistency problem. Meanwhile, multiple cost centres within one utility make is harder to gain sufficient information about the full range of productivity parameters along which the sliding scale must be defined. In contrast, the price cap only requires detailed knowledge about the least productive firm (although some knowledge of the range is presumably necessary in order to identify this firm). These are clearly important areas for future research.

Other omissions from our model may, however, have favoured price cap regulation. Thus, for example, we have ignored issues of quality regulation and the uncertainty about costs or demand that both regulator and firm might face after having designed and selected from the sliding scale menu respectively. In the former case, the price cap's sharp incentives for cost-reduction are often claimed to be damaging (see Armstrong *et al.* (1994)), while on the latter, Burns *et al.* (1995) suggest that the sliding scale provides for a suitable sharing of any risk between the parties. A further issue, raised by the Utilities Act 2000 concerns distributional matters between the regulated firm and its customers. The Act places a prior duty on regulators to design policy with consumer interests foremost in mind (i.e. to place additional weight on consumer surplus in our model). This is likely to increase the welfare gains available from the sliding scale because, as we have seen, it allows regulators to adjust prices (and efforts) in order to extract rent from the firm. This does not happen with price caps, where the need to ensure sustainability of the firm guarantees substantial rents in the event that the firm has low costs.

It seems clear additional research can help identify the most appropriate method of regulating utilities prices. In the meantime, our results suggest that sliding scale regulation may prove a useful tool. We also believe that the current paper has indicated how a combination of theory and estimation-based simulation may be useful in evaluating the available regulatory alternatives.

Appendix

A The First-Best solution

To solve the program in Section 2, let $\nu \geq 0$ be the shadow price associated with the IR constraint. Define the Lagrangian

$$\mathcal{L}(e,q) = B(q) - R(q) + U(e,q) + \nu[R(q) - C(e,q) - \psi(e)] \tag{A.1}$$

The Kuhn-Tucker first-order conditions are

$$e \;:\; \psi'(e) = q \tag{A.2}$$
$$q \;:\; B'(q) - R'(q) + \nu[R'(q) - C_q] = 0 \tag{A.3}$$
$$CS \;:\; \nu U = 0 \tag{A.4}$$

Equation (A.2) equates the marginal disutility of effort with its marginal benefit and, similarly, (A.3) equates the marginal benefit of output with its marginal cost. Equation (A.4) is the complementary-slackness condition. Using the fact that the gross consumer surplus is defined by

$$B(q) = \int_0^q P(q')\, dq' \tag{A.5}$$

we have that $B'(q) = P(q)$. Using this result (A.3) can be written

$$L = \frac{p - C_q}{p} = \frac{\nu}{(1+\nu)\eta} \tag{A.6}$$

where L is the Lerner index and $\eta = -pD'/q$ is the absolute value of the elasticity of demand. For the IR constraint to be satisfied at positive levels of effort we must have $p > C_q$. Hence, from (A.6), $\nu > 0$ and, from the CS condition, $U = 0$; i.e. the IR constraint binds. Solving (A.6), $U(e, q) = 0$, $p = P(q)$ gives e, q and p at the First-Best.

B A note on form of the cost function

The numerical implementation of the sliding scale requires functional forms for $D(q)$ and $f(\beta)$. We have already commented on these in the text. In addition, we have restricted the distributor's cost function to be linear in effort and output and the disutility of effort function to $\psi(e) = \gamma e^2/2$. Each of these requires comment.

A more general version of (1) than the one we have used would be

$$C = \alpha + [\beta - \phi(e)]q \tag{B.7}$$

where $\phi(0) = 0, \phi' > 0, \phi'' \leq 0$. Using a more general $\psi(e)$ function and assuming that the price cap is in place (as does our empirical procedure), a rent-maximising distributor would choose e such that

$$\psi'(e) = \phi'(e)q \tag{B.8}$$

Expanding as a Taylor series and using $\phi(0) = \psi(0) = 0$ we have

$$\psi(e) = b_0 e + \frac{1}{2} b_1 e^2 + \cdots \tag{B.9}$$

$$\phi(e) = a_0 e + \frac{1}{2} a_1 e^2 + \cdots \tag{B.10}$$

Equation (B.8) then becomes

$$b_0 + b_1 e = (a_0 + a_1 e)q \tag{B.11}$$

with solution $e = e(q)$. Under the assumption that zero effort corresponds to zero output ($e(0) = 0$) we have that $b_0 = 0$ and hence from (B.11)

$$e(q) = \frac{a_0}{b_1} q + \text{terms in } q^2 \text{ and higher}$$

By appropriate choice of units we can put $a_0 = 1$ and in the notation of the model we have that $b_1 = \gamma$. Using this, the average variable cost for REC i at time t is

$$\frac{V_{it}}{q_{it}} = \beta_{it} - \frac{q}{\gamma} + \text{terms in } q^2 \text{ and higher} \tag{B.12}$$

Our estimation procedure tests (B.12) and finds no support for including the quadratic terms in output. Hence, $\psi(e) = \frac{\gamma e^2}{2}$ and $\phi(e) = e$ are consistent with our data.

C Details of the simulation procedure

We analyse the system of equations in Section 4 using a series of MATLAB subroutines. The structure of our procedure is as follows:

1. For a given value of $U(\underline{\beta}) = \underline{U}$ solve the equations

$$
\begin{aligned}
(\underline{p} - \underline{\hat{c}})D(\underline{p}) - \alpha &= \underline{U} + \frac{\gamma}{2}\underline{e}^2 \\
\underline{e} &= D(\underline{p})/\gamma \\
\underline{\hat{c}} &= \underline{\beta} - \underline{e} \\
\underline{k} &= \frac{D(\underline{p})}{D(\underline{p}) + (\underline{p} - \underline{\hat{c}})D'(\underline{p})}
\end{aligned}
$$

2. Given $\underline{v} = \underline{v}(\underline{U})$ and $W(\underline{\beta}) = 0$, solve the system of differential equations (24). This gives trajectories for v as functions of $\underline{U}$. In particular we get $U(\overline{\beta}) = \theta(\underline{U})$.

3. Solve $\theta(\underline{U}) = 0$ to obtain the initial boundary value $\underline{U}$.

D Data sources

At privatization in 1989, the electricity industry of England and Wales was organised into twelve regional electricity companies (RECs) each having an exclusive licence to distribute electricity to customers in a specific geographical area. Measures were taken to ensure that even if the RECs were taken over by new owners, separate accounts would be kept of the regulated components of the businesses thereby ensuring a consistent record for regulatory purposes. It is only since privatization that electricity distribution has been subject to price capping regulation and, since equation (30) depends on the impact of such regulation, we are confined to the period since the start of the 1990s for the cost function estimation.

Two alternative sources of data are available for cost estimation. The Office for Electricity Regulation (OFFER—now part of OFGEM) conducted an analysis of regulatory accounts in the recent review of public electricity suppliers (OFFER (1999a)) This is a detailed investigation of accounting procedures and attempts to adjust the accounts for differences in treatment of a large number of items. Unfortunately, the analysis only extends back to 1993, and without detailed information of the sort only available to the regulator, it is impossible to make appropriate amendments to previous data. In addition certain procedures adopted by OFFER are disputed by the industry, so that to date there exists no agreed reconstruction of the accounts. The alternative is to take the collected raw accounts as made available by the Centre for Regulated Industries (see Board (1999)). These are available from 1990/91, and provide details of distribution operating costs and amounts of electricity distributed. This gives a total of ten years of data are available from this source. In view of the longer data set and minimum consistency imposed by the electricity legislation, we based our analysis of costs on the published accounts. In all 96 usable observations were available.

Electricity demand data were taken from the Centre for Regulated Industries and Handbooks of Electricity Supply Statistics. GDP data for each REC area were obtained from Business Strategies Limited (BSL).[21] This series was obtainable back to 1982/83. Therefore, the dataset covers each REC for the period 1982/83 to 1996/97. The nominal electricity prices for each REC were based on the prices for representative cities within each REC area taken from various issues of the Digest of UK Energy Statistics (DUKES). The real electricity prices were computed by deflating the nominal prices for each REC by the RPI. The twelve RECs are numbered as follows:

No.	REC
1	LEB
2	SEEBOARD
3	Southern
4	SWEB
5	Eastern
6	East Midlands
7	MEB
8	SWALEC
9	MANWEB
10	Yorkshire
11	Northern
12	NORWEB

[21]We are grateful to Neil Blake for assistance in obtaining regional GDP data.

References

Armstrong, M., Cowan, S., and Vickers, J. (1994). *Regulatory Reform: Economic Analysis and British Experience*. MIT Press, Cambridge, Massachusetts.

Armstrong, M., Cowan, S., and Vickers, J. (1995). Nonlinear pricing and price-cap regulation. *Journal of Public Economics*, **58**, 33–55.

Auriol, E. and Laffont, J.-J. (1993). Regulation by duopoly. *Journal of Economics and Management Strategy*, **1**(3), 507–533.

Bernstein, J. I. and Sappington, D. E. M. (1999). Setting the X-factors in price-cap regulation. *Journal of Regulatory Economics*, **16**(1), 5–25.

Bernstein, J. I. and Sappington, D. E. M. (2000). How to determine the X in RPI-X regulation: A user's guide. *Telecommunications Policy*, **24**(1), 63–68.

Burns, P., Turvey, R., and Weyman-Jones, T. G. (1995). Sliding scale regulation of monopoly enterprises. Centre for the Study of Regulated Industries, University of Bath, Discussion Paper 11.

Burns, P., Turvey, R., and Weyman-Jones, T. G. (1998). The behaviour of the firm under alternative regulatory constraints. *Scottish Journal of Political Economy*, **45**(2), 133–157.

Dobbs, I. (2004). Intertemporal price cap regulation under uncertainty. *Economic Journal*, **114**, 421–440.

DTI (1999). *A Fair Deal for Consumers: Modernising the Framework for Utility Regulation*. Department of Trade and Industry, London. HMSO: Cm 3898.

Gasmi, F., Ivaldi, M., and Laffont, J.-J. (1994). Rent extraction and incentives for efficiency in recent regulatory proposals. *Journal of Regulatory Economics*, **6**, 151–176.

Gasmi, F., Laffont, J.-J., and Sharkey, W. W. (1997). Incentive regulation and the cost structure of the local telephone exchange network. *Journal of Regulatory Economics*, **12**, 5–25.

Gasmi, F., Kennet, D. M., Laffont, J.-J., and Sharkey, W. W. (2002). *Cost Proxy Models and Telecommunications Policy: A New Empirical Approach to Regulation*. MIT Press, Cambridge, Massachusetts.

Green, R. (1999). The electricity contract market in England and Wales. *Journal of Industrial Economics*, **47**(1), 107–124.

Green, R. and McDaniel, T. (1998). Competition in electricity supply: Will '1998' be worth it? *Fiscal Studies*, **19**(3), 273–293.

Jamasb, T., Nillesen, P., and Pollitt, M. G. (2004). Strategic behaviour under regulatory benchmarking. *Energy Economics*, **26**, 825–843.

Laffont, J.-J. and Tirole, J. (1993). *A Theory of Incentives in Procurement and Regulation*. MIT Press, Cambridge, Massachusetts.

Laffont, J.-J., Maskin, E., and Rochet, J.-C. (1987). Optimal non-linear pricing with two-dimensional characteristics. In T. Groves, R. Radner, and S. Reiter, editors, *Information, Incentives and Economic Mechanisms: Essays in Honour of L. Hurwicz*. University of Minnesota Press: Minneapolis.

Mayer, C. and Vickers, J. (1996). Profit-sharing regulation: An economic appraisal. *Fiscal Studies*, **17**(1), 1–18.

Newbery, D. M. (1998). Competition, contracts and entry in the electricity spot market. *RAND Journal of Economics*, **29**(4), 726–749.

Newbery, D. M. and Pollitt, M. G. (1997). The restructuring and privatisation of Britain's CEGB: Was it worth it? *Journal of Industrial Economics*, **45**(1), 269–303.

OFFER (1999a). *Review of Public Electricity Suppliers 1998 to 2000: Distribution Price Control Review (Consultation Paper).* Office for Electricity Regulation, London.

OFFER (1999b). *Review of Public Electricity Suppliers 1998 to 2000: Distribution Price Control Review (Draft Proposals).* Office for Electricity Regulation Markets, London.

OFGEM (2000). *The Structure of Electricity Distribution Charges: Initial Consultation Paper*. Office of Gas and Electricity Markets, London.

OFGEM (2004a). *Domestic Competitive Market Review 2004*. Office of Gas and Electricity Markets, London.

OFGEM (2004b). *Electricity Distribution Price Control Review: Final Proposals*. Office of Gas and Electricity Markets, London.

Pesaran, H., Smith, R. P., and Akiyama, T. (1998). *Energy Demand in Asian Developing Economies*. Oxford Univeristy Press, Oxford, UK.

Schmalensee, R. (1989). Good regulatory regimes. *RAND Journal of Economics*, **20**(3), 417–436.

Utilities Journal (2000). Editorial: Incentivising regulation.

Wilson, R. B. (1993). *Nonlinear Pricing.* Oxford Univeristy Press, Oxford, UK.

Wolfram, C. D. (1998). Strategic bidding in a multiunit auction: An empirical analysis of bids to supply electricity in England and Wales. *RAND Journal of Economics*, **29**(4), 703–725.

Wolfram, C. D. (1999). Measuring duopoly power in the British electricity spot market. *American Economic Review*, **89**(4), 805–826.

Table 1: Electricity average variable distribution cost estimates

Variable	C1	C2	C3	C4
Constant	3.2143**	2.1493**	3.9451**	2.6344**
q	-12.2925**	-4.4067**	-16.7358**	-6.5532**
q^2	14.3202		18.7752*	
Time trend			0.0048	-0.0003
No. of REC dums	11	11	11	11
No. of Time dums	9	9		
Diagnostics				
Degs. of freedom	97	98	105	106
Adjusted R^2	0.674	0.671	0.615	0.606
Amemiya pred.	-4.42	-4.41	-4.31	-4.29
Akaike info.	-1.58	-1.58	-1.47	-1.46
RESET(1)	$\boldsymbol{F_{(1,96)} = 14.79}$	$\boldsymbol{F_{(1,97)} = 13.62}$	$F_{(1,104)} = 3.85$	$F_{(1,105)} = 3.74$
Normality	$\boldsymbol{\chi^2_2 = 10.68}$	$\chi^2_2 = 5.59$	$\boldsymbol{\chi^2_2 = 7.58}$	$\chi^2_2 = 5.25$
Test of zero restrictions on:				
All variables	$F_{(22,97)} = 12.20$	$F_{(21,98)} = 12.53$	$F_{(14,105)} = 14.55$	$F_{(13,106)} = 15.11$
REC dums	$F_{(11,97)} = 6.16$	$F_{(11,98)} = 6.17$	$F_{(11,105)} = 5.77$	$F_{(11,106)} = 5.58$
Time dums	$F_{(9,97)} = 3.08$	$F_{(9,98)} = 3.19$		

Notes: [1] All equations are estimated in LIMDEP 7. [2] Time period is 1990/01–1999/2000. [3] t-statistics and probabilities are based upon standard errors corrected for heteroskedasticity. [4] * and ** indicate that a coefficient is significantly different from zero at the 10% and 5% levels respectively. [5] Bold type indicates a failure of a diagnostic test at the 5% level.

Table 2: Electricity demand model estimates by REC

Variables	D1	D2	D3	D4
$\log h$	0.1868**	0.1626**	0.1482**	0.1606**
$\log p_1$	-0.2391**	-0.0727**	-0.1885**	-0.2513**
$\log p_2$	-0.1319*	0.0703	-0.0911	-0.1640**
$\log p_3$	-0.1714**	0.0224	-0.1333**	-0.2016**
$\log p_4$	-0.1186*	0.0605	-0.0853	-0.1473**
$\log p_5$	-0.2280**	-0.0282	-0.1836**	-0.2555**
$\log p_6$	-0.1905**	0.0456	-0.1419*	-0.2267**
$\log p_7$	-0.1802**	0.0360	-0.1383**	-0.2152**
$\log p_8$	0.0438	0.2381**	0.0800	-0.0115R
$\log p_9$	-0.1644	0.0683	-0.1174	-0.1996**
$\log p_{10}$	-0.0127	0.2218*	-0.0435	-0.1220
$\log p_{11}$	-0.1100	0.0786	-0.1309**	-0.1959**
$\log p_{12}$	-0.2335**	-0.0080	-0.1862**	-0.2659**
Time trend		0.0005		
$\log q(-1)$	0.7426**	0.7333**	0.7850**	0.7694**
Constant	-0.5909**	-0.9731**	-0.4803**	-0.3903**
Dum REC 8:1988/89			0.0279**	0.0277**
Dum REC 10:1984/85			-0.0382**	-0.0365**
Dum REC 10:1989/90			0.0271**	0.0289**
Dum REC 10:1990/90			-0.0564**	-0.0548**
Dum REC 11:1984/85			0.0279**	0.0278**
Dum REC 11:1989/90			-0.0411**	-0.0409**
No. of REC dums	11	11	11	11
No. of Time dums	13		13	13
Diagnostics				
Degs. of freedom	129	141	123	124
Adjusted R^2	0.998	0.997	0.999	0.999
Amemiya pred.	-8.55	-8.22	-8.92	-8.92
Akaike info.	-5.72	-5.38	-6.09	-6.09
Error autocorr(1)	$F_{(1,117)} = 3.52$	$\boldsymbol{F_{(1,128)} = 10.05}$	$F_{(1,111)} = 2.08$	$F_{(1,112)} = 1.87$
RESET(1)	$F_{(1,128)} = 2.00$	$\boldsymbol{F_{(1,140)} = 4.41}$	$F_{(1,122)} = 1.67$	$F_{(1,123)} = 0.62$
Normality	$\boldsymbol{\chi^2_2 = 12.21}$	$\chi^2_2 = 3.37$	$\chi^2_2 = 0.08$	$\chi^2_2 = 0.48$
Test of zero restrictions on:				
All variables	$F_{(38,129)} = 2260.6$	$F_{(26,141)} = 2223.7$	$F_{(44,123)} = 2897.9$	$F_{(43,124)} = 2652.4$
REC dums	$F_{(11,129)} = 2.76$	$F_{(11,141)} = 2.36$	$F_{(11,123)} = 3.30$	$F_{(11,124)} = 3.22$
Time dums	$F_{(13,129)} = 6.21$		$F_{(13,123)} = 9.27$	$F_{(13,124)} = 12.67$
Test of coefficient restrictions:				
Against D3	$\boldsymbol{F_{(6,168)} = 15.56}$			$F_{(1,168)} = 2.26$

Notes: [1] All equations are estimated in LIMDEP 7. [2] Time period is 1982/83–1996/97. [3] t-statistics and probabilities are based upon standard errors corrected for heteroskedasticity. [4] * and ** indicate that a coefficient is significantly different from zero at the 10% and 5% levels respectively. [5] 'R' for REC 8 (in D4) indicates a constrained coefficient—see Section 5.2.2. [6] Bold type indicates a failure of a diagnostic test at the 5% level. [7] The absolute values of the estimated long-run price elasticities are given in Table 3 (column 8). [8] The estimated long-run income elasticities are 0.733, 0.61, 0.69 and 0.70 for models D1, D2, D3 and D4 respectively.

Table 3: Summary of parameter values

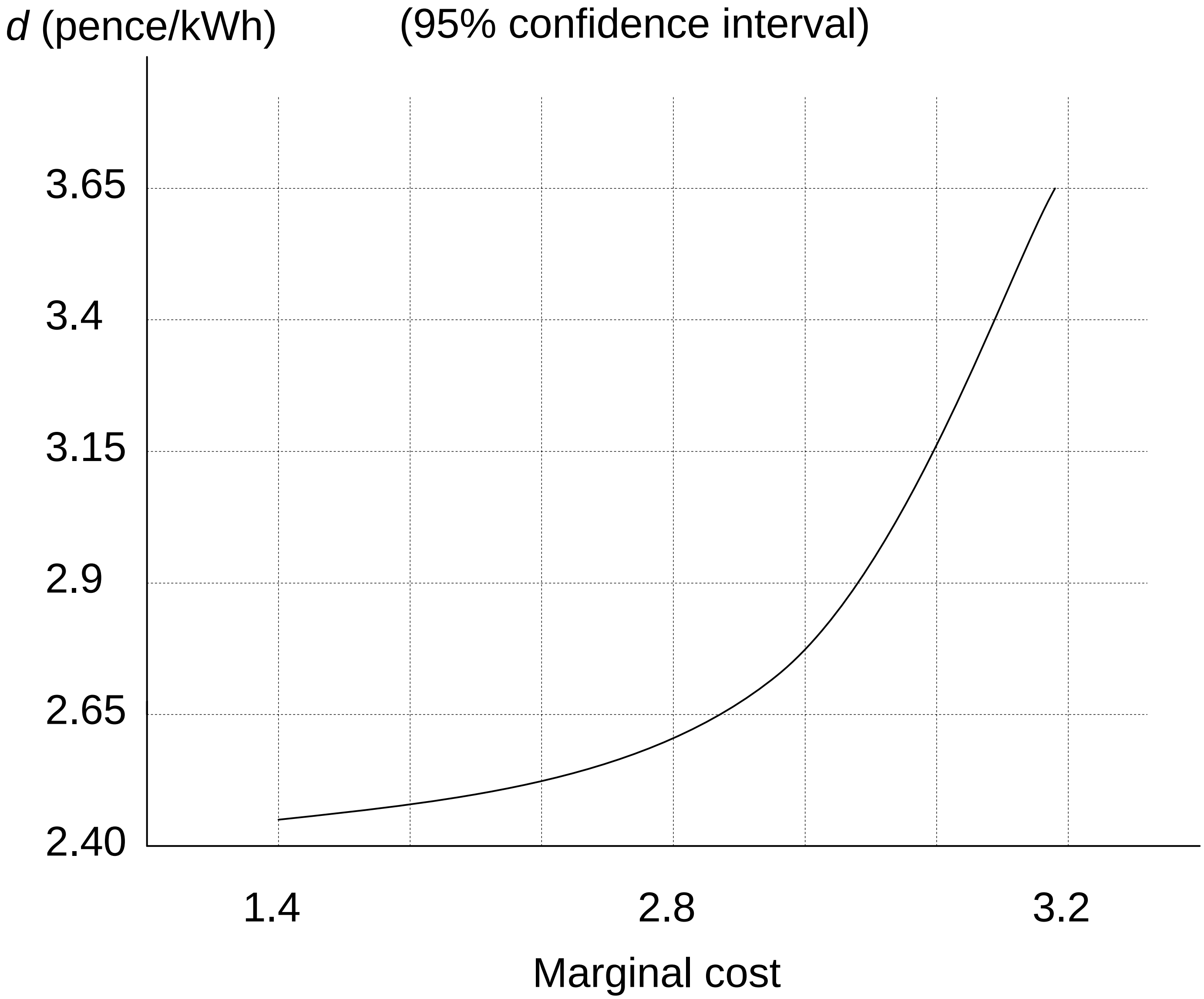
REC	b_i	s.e.	Range 1 (95% c.i.)		Range 2 (99% c.i.)		γ	η_i	A_i	z_i	α_i
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
1	2.58	0.30	2.00	3.17	1.81	3.36	1.50	1.09	3.27	5.6	0.78
2	2.32	0.26	1.80	2.84	1.63	3.01	1.50	0.71	2.48	5.6	0.60
3	2.73	0.40	1.94	3.53	1.68	3.79	1.50	0.87	3.96	5.6	1.18
4	2.19	0.18	1.82	2.56	1.70	2.67	1.50	0.64	1.74	5.9	0.58
5	3.00	0.45	2.11	3.89	1.82	4.18	1.50	1.11	4.91	5.5	0.82
6	2.64	0.36	1.93	3.35	1.70	3.58	1.50	0.98	3.73	5.7	0.93
7	2.61	0.35	1.90	3.31	1.68	3.54	1.50	0.93	3.64	5.7	0.87
8	2.03	0.16	1.72	2.34	1.62	2.44	1.50	0.05	1.13	6.0	0.63
9	2.19	0.25	1.68	2.69	1.52	2.85	1.50	0.87	2.70	6.3	0.72
10	2.48	0.33	1.83	3.12	1.62	3.33	1.50	0.53	2.87	5.9	0.63
11	2.14	0.21	1.72	2.57	1.58	2.70	1.50	0.85	2.15	6.0	0.46
12	2.63	0.32	1.99	3.28	1.78	3.48	1.50	1.15	3.69	5.6	0.73

Notes: Input price (z) is in pence/kWh and is defined for REC i as $z_i = p_i - d_i$, where p_i is the consumer price of electricity and d_i is the distribution price. A unit of output (A) is in 10^{10} kWh/year. Thus, if $p_1 = 7.3$p/kWh, annual revenue for REC 1 would be $d_1 \times q_1 = (p_1 - z_1) \times A_1 \times p_1^{-1.09} \times 10^{10} = 1.7 \times 3.27 \times 7.3^{-1.09} \times 10^{10}$pence $\approx$ £64m. Further, α_i above, and rent and transfers in the figures that follow, are measured in £10^2m per year.

Table 4: Welfare gains from the sliding scale

REC	G for Range 1	G for Range 2
1	40.6%	57.0%
2	22.4%	43.0%
3	51.7%	64.5%
4	14.1%	32.8%
5	44.9%	57.2%
6	31.2%	38.5%
7	42.4%	58.5%
8	11.1%	26.6%
9	27.3%	47.0%
10	23.3%	43.9%
11	18.2%	38.5%
12	43.0%	58.5%
Average	30.8%	48.3%

Figure 1a: REC 1 sliding scale
(95% confidence interval)



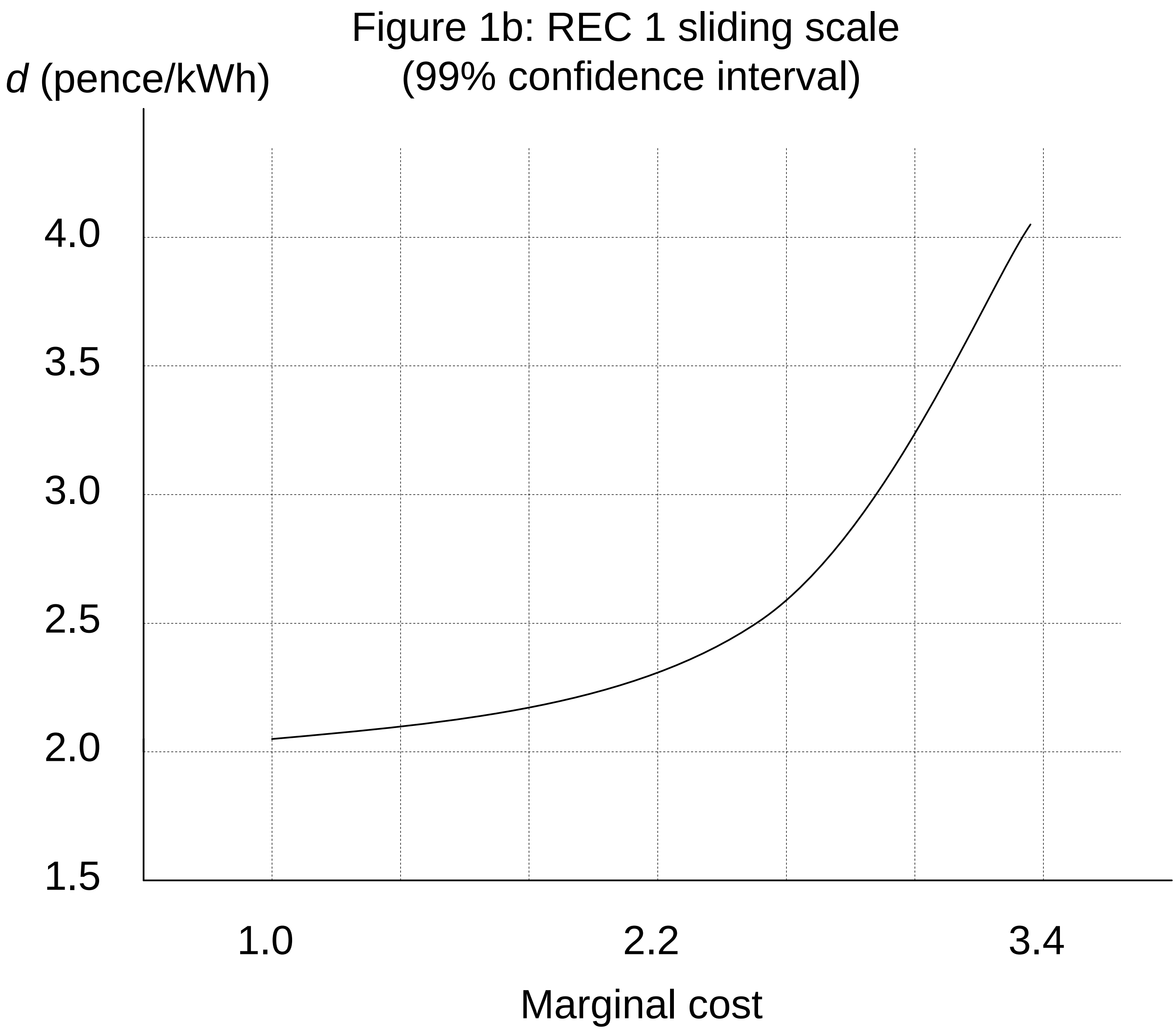


Figure 1b: REC 1 sliding scale
(99% confidence interval)
d (pence/kWh)
4.0
3.5
3.0
2.5
2.0
1.5
1.0
2.2
3.4
Marginal cost

Figure 2a: REC 1 transfer
(95% confidence interval)

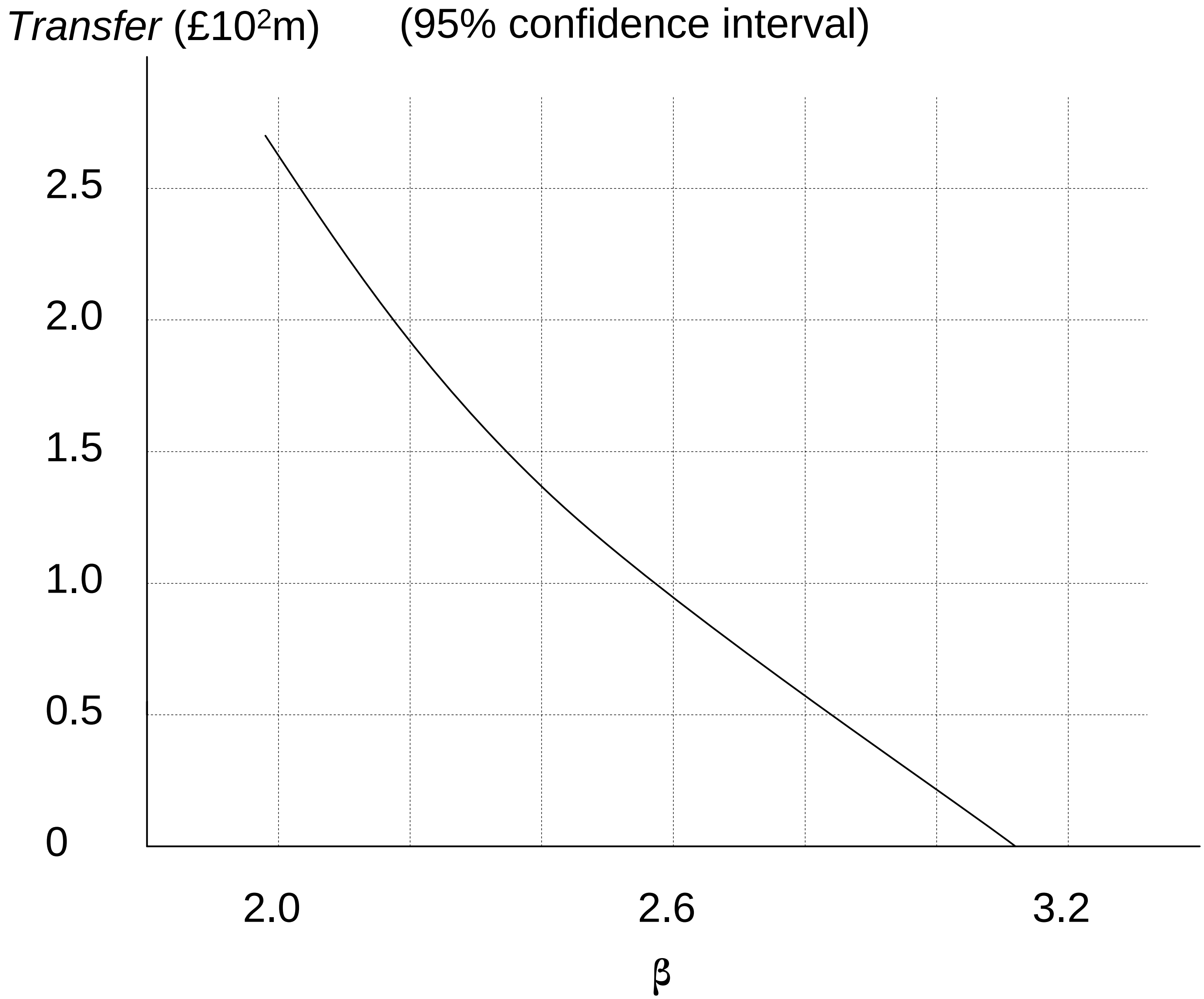


Figure 2b: REC 1 transfer (99% confidence interval)

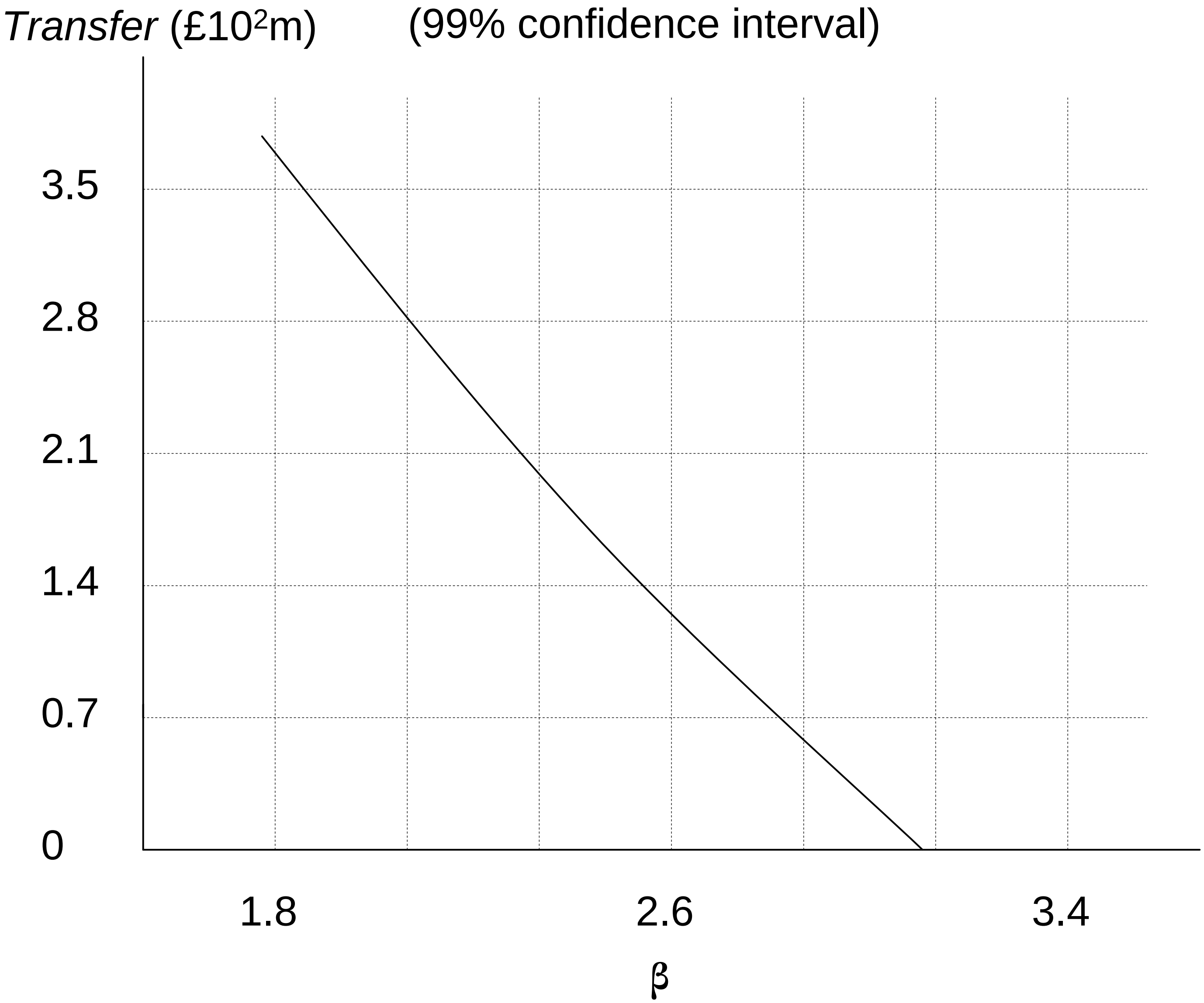
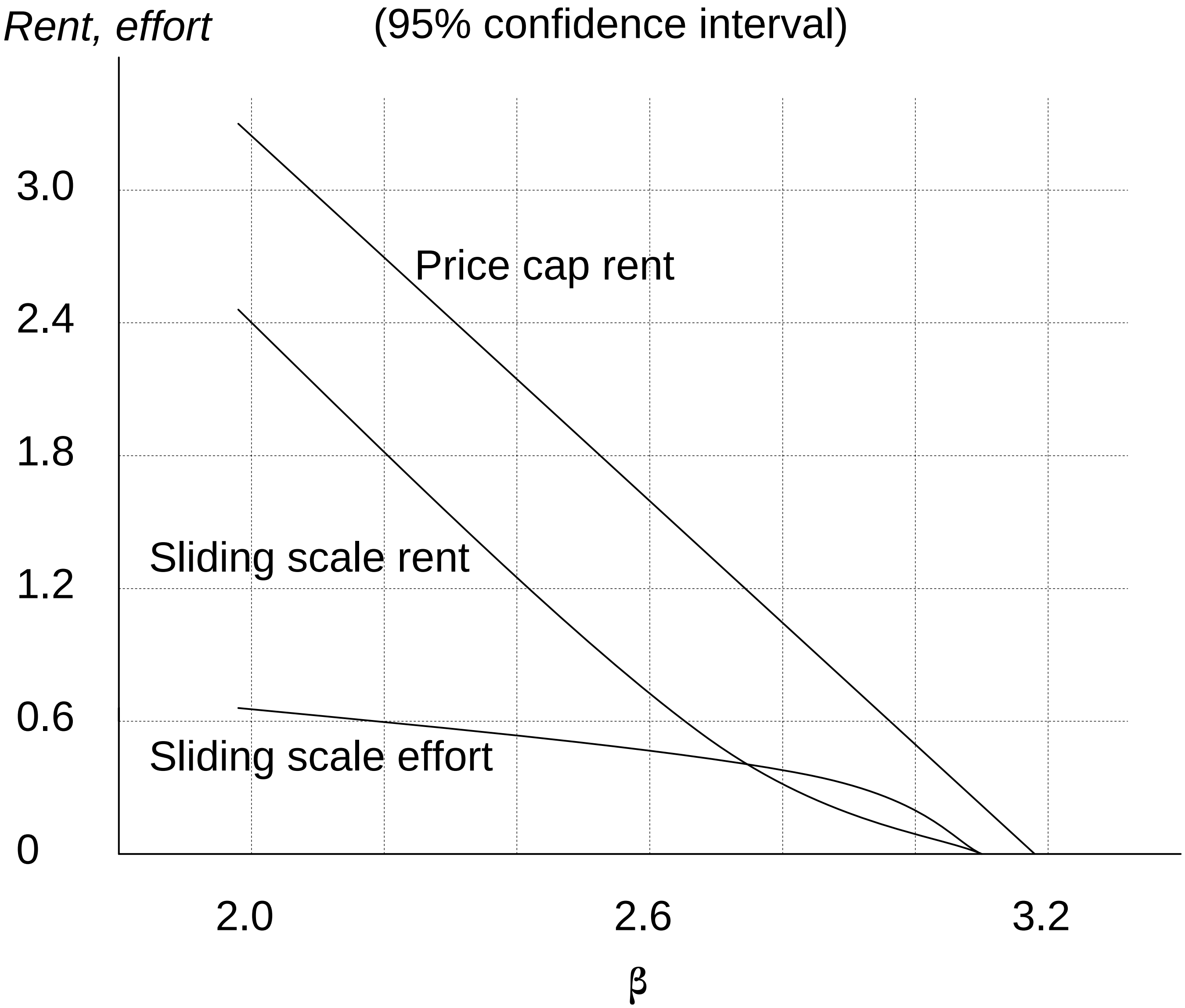


Figure 3a: REC 1 rent and effort
(95% confidence interval)



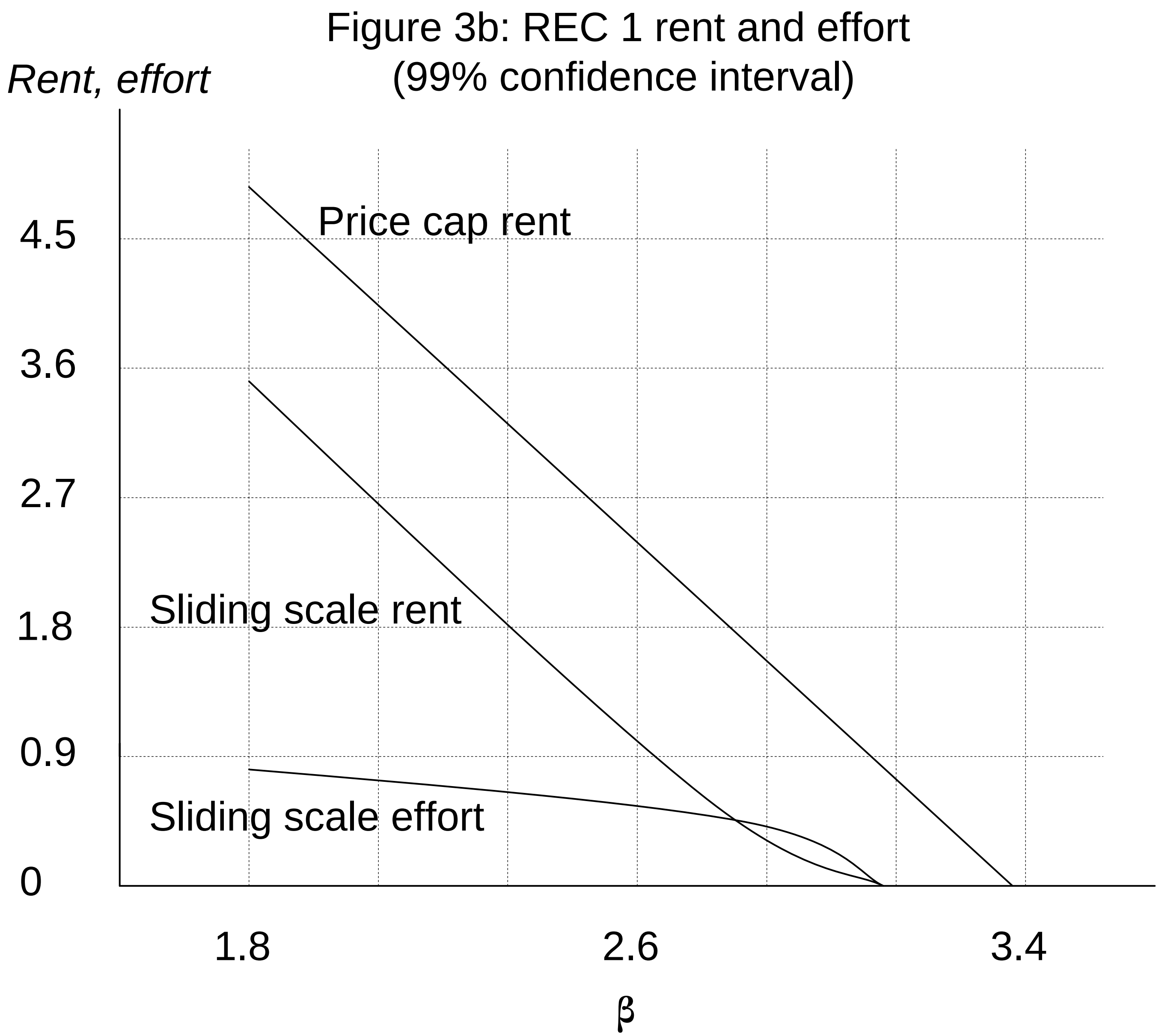


Figure 3b: REC 1 rent and effort
(99% confidence interval)
Rent, effort
4.5
3.6
2.7
1.8
0.9
0
Price cap rent
Sliding scale rent
Sliding scale effort
1.8
2.6
3.4
β

Figure 4a: REC 1 consumer prices
(95% confidence interval)

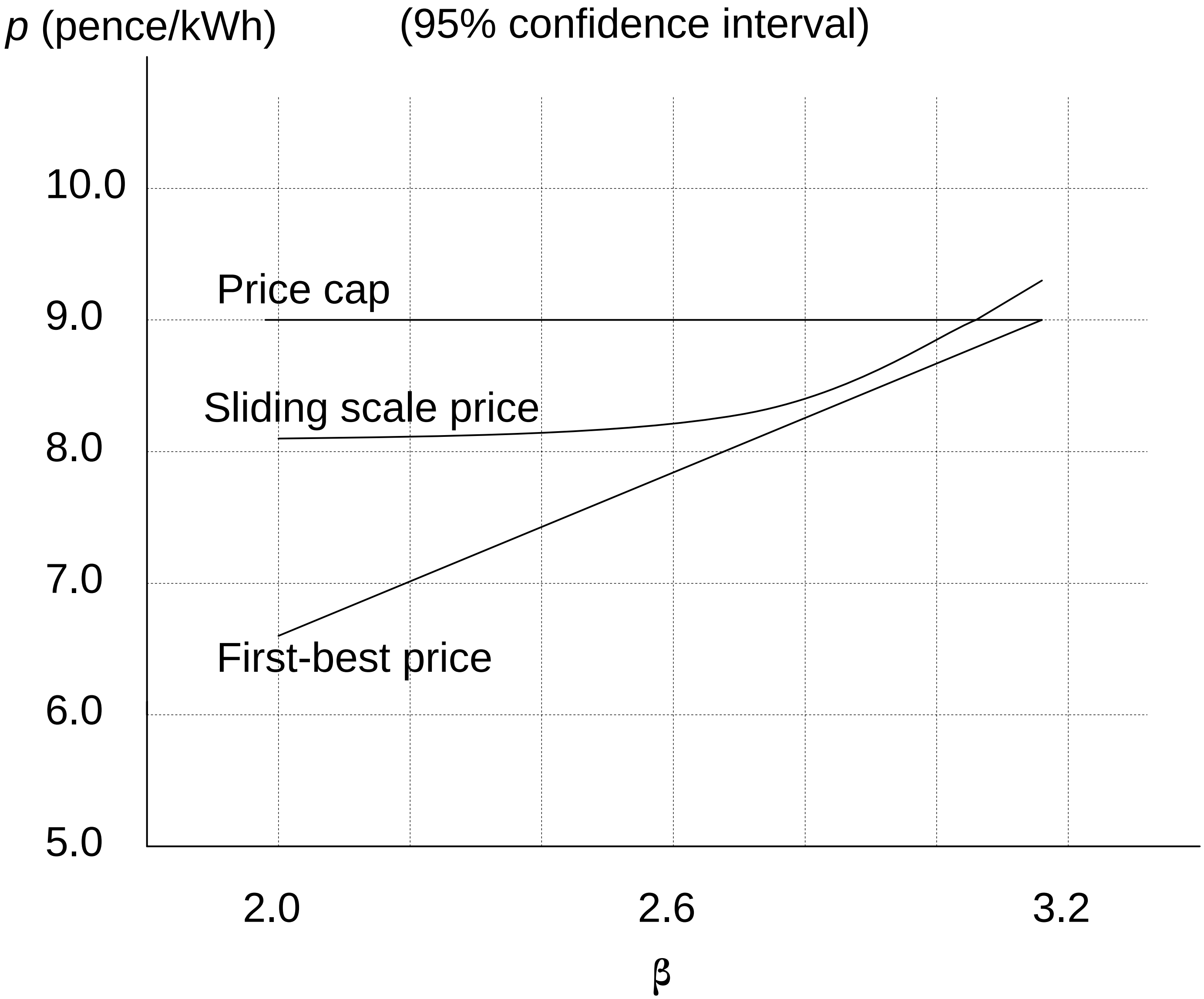


Figure 4b: REC 1 consumer prices
(99% confidence interval)