Exploring the determinants of "best practice" in network regulation: The case of the electricity industry

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Abstract

In this paper we use a best practice index constructed from the survey responses of regulators in 40 countries to explore the determinants of outcomes in electricity network regulation. We construct a model of explained behaviour where we are particularly interested in understanding the impact of industry setting, political, and economic environments on the degree of best practice regulation. Our results suggest that political and economic institutions as well as the behaviour of regulators in neighbouring countries/states may be important determinants of outcomes; this also leads us to question whether one "best practice" model is in fact applicable to countries with very different political and economic contexts.

Key Words: Network regulation; Electricity; Efficiency analysis; Institutions

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1 Introduction

Although incentive regulation of energy networks is now widespread, the same cannot be said for best practice in the application of associated benchmarking methods. In our earlier paper (Haney and Pollitt, 2009), we presented the results of an international survey of energy regulators in 40 countries conducted between June and October 2008. The regulators were drawn from Europe, South America and Australasia.[2] Evidence from our survey suggests that there is a wide variety of methods being implemented internationally; very few countries adhere closely to best practice principles as defined by Lovell (2006); and there are interesting regional effects at work where regulators appear to be influenced by their neighbours' paths.[3]

In this paper we formalise the lessons from the summary responses of regulators to our survey by developing a model for best practice in efficiency analysis. We focus on the electricity industry where we have the most survey responses. We use the best practice index developed in our earlier paper to investigate which sector and institutional characteristics have the most significant effects on the implementation of advanced regulatory techniques.

Our best practice index variable is based on Lovell's identification of best practice indicators for efficiency analysis (Lovell 2006). The original index ranges from 0 to 8, where the highest score indicates the presence of all best practice elements in the regulatory process.[4] Our choice of best practice indicators allows us to evaluate the use a set of advanced benchmarking techniques (data envelopment analysis (DEA); corrected ordinary least squares (COLS); stochastic frontier analysis (SFA); we also investigate how widespread the latest advances in these techniques have become, for example the incorporation of environmental factors, dealing with uncertainty, and using international and panel data. In the analysis to follow, we use a condensed form of the index so that we have four categories of best practice ranging from very basic to high, as summarised in *Table 1*.

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[2] The US and Canada were deliberately excluded from the survey due to the different nature of regulation in these countries, which tends to not involve comparative benchmarking of company performance, for historic reasons.

[3] There are sometimes detailed legal restrictions on the techniques that can be used by regulators (e.g. in Germany). However these restrictions are unlikely to be exogenous and more likely a reflection of the institutional factors that we examine.

[4] For the original scoring system and a list of best practice scores by country, see Tables A1 and A2 in the Appendix. This shows that countries that use reference models rather than frontier efficiency techniques tend to have low scores (e.g. Chile and Sweden), but we attempt to test the factors which might be relevant to this (e.g. ratio of social science to engineering graduates). Our score is the average of the score for electricity transmission and electricity distribution. For more details and a discussion of the index construction see Haney and Pollitt (2009).

Table 1: Best practice index

Category	*Original Index*	*Best Practice Index (BPI)*
Very Basic (VB)	0 ≤ **VB** < 2	1
Basic (B)	2 ≤ **B** < 4	2
Intermediate (I)	4 ≤ **I** < 6	3
High (H)	6 ≤ **H** ≤ 8	4

We are particularly interested in exploring and providing evidence of how political and economic institutions have an impact on regulatory outcomes. The literature on the role of institutions in shaping and structuring incentives for economic, political and social outcomes is vast. Acemoglu has written prolifically on this subject (see for example Acemoglu 2003; 2006) and we draw some ideas in particular from his work with Johnson and Robinson (Acemoglu, Johnson et al. 2005). Finally, the results of our analysis lead us to question the concept of "best practice" and to look to the work of Rodrik on second-best institutions and the importance of country context (Rodrik 2008). It is also important to note upfront however that the use of best practice methods is no guarantee of best practice outcomes (e.g. Guasch et al., 2007). However given that the quality of institutions is a key determinant of economic development, it is interesting to focus on use of "best practice" methods by institutions (Easterly and Levine, 2003).

2 Best practice model

The construction of our model of explained behaviour is based on the basic idea that a regulator's choice of methods is constrained by a range of factors. Following Domah, Pollitt et al. (2002) we group these factors into three main categories: industry setting; economic environment; and political environment so that our model for Country *i* becomes:

Equation 1

Best practice $_i$ = *f* (Industry setting, Economic environment, Political environment)

2.1 Industry setting

We would expect the size, complexity and efficiency of the electricity network to have an important impact on the choice of regulatory methods. In general, it is easier for countries with larger numbers of distribution and transmission companies to benchmark performance than for those with limited numbers.

Equation 2

Industry setting = g $_i$ (Number of regulated companies; Electricity consumption; Transmission and Distribution losses)

In our analysis we use the total number of regulated electricity distribution and transmission companies in its natural log to account for decreasing returns. We use a measure of transmission and distribution losses as a percentage of output to reflect different levels of system efficiency across countries and to account for the size of the electricity market we use total electricity consumption, again in natural log form[5].

2.2 Economic environment

We know that countries have taken various approaches to regulating their electricity networks, but we are lacking a systematic explanation for the variety of paths chosen. Some of the differences are indeed due to the characteristics of the industry in terms of size, number of regulated companies and size of customer base. However, we would expect there to be additional factors at work, particularly those involving institutions.

Following Acemoglu, Johnson and Robinson (2005) and Rodrik et al. (2004), we consider institutions to be fundamental in shaping and structuring incentives for economic, political and social outcomes. In terms of economic institutions, the structure of property rights and the presence and perfection of markets are central (Acemoglu, Johnson et al. 2005). At the micro level in the context of electricity networks, economic institutions shape the incentives of actors in the industry to invest, adopt new technologies and organise production. In some countries economic institutions will foster growth while in others they have the potential to hinder growth and innovation.

Equation 3

Economic environment = h $_i$ (GDP per capita; ratio of social science to engineering graduates; Ease of registering property; Privatisation)

In our analysis, we use the natural log of GDP per capita; a variable that captures the ratio of social science to engineering graduates[6]; a measure of ease of property registration[7]; and a measure of privatisation based on the level of government enterprises and investment[8].

[5] Data on company numbers comes from our 2008 survey; data on losses and electricity consumption is for the year 2005 and comes from the World Development Indicators accessed through ESDS International.

[6] The variable we use is the ratio of social science, business and law graduates to engineering, manufacturing and construction. The data comes from the UNESCO Institute of Statistics for the year 2006 or the most recent year and is available from http://www.uis.unesco.org/ev_en.php?ID=2867_201&ID2=DO_TOPIC

[7] We use the registering property indicator from the World Bank Doing Business Report 2009. This is a ranking of developing and developed countries in terms of the ease of registering property.

[8] Here we use a government enterprises and investment index from the Economic Freedom of the World 2008 report. The index is a zero to 10 rating composed using data on the number, composition and share of output

2.3 Political environment

Political institutions have direct and indirect impacts on economic institutions (Acemoglu, Johnson et al. 2005). In the case of electricity networks, the form of political power can have a strong impact on the type of regulatory environment that exists. For example, if there is a lack of restraint on arbitrary government action (possibly due to the presence of corruption or the lack of explicit separation of legislative, executive and judicial powers), the credibility of the regulatory regime is negatively affected. This may constrain the regulator from choosing an advanced method of incentive regulation, particularly due to the challenge of collecting data from regulated companies. If the regulator is not credible, the incentives for companies to submit information are reduced and this places a severe limitation on options (Burns, Jenkins et al. 2006). We use Transparency International's 2008 Corruption Perception Index to investigate this effect, where a country can score between 0 (highly corrupt) and 10 (highly clean).[9]

The credibility of a regulatory agency can also be enhanced by its independence from government. Independent regulatory agencies are an important and now widespread feature of regulation internationally. Although there are considerable differences in the extent of independence across countries (see for example Gilardi 2002; Gilardi 2008), in our analysis we focus on the length of time an independent electricity regulator has been established in order to measure experience and learning.

Equation 4

Political environment = i $_i$ (corruption; age of independent regulator; average regional index; region)

We use the number of years to the end of 2008 since the creation of an independent regulator for this purpose[10]. Neighbourhood effects have been explored in the theoretical social science literature in significant detail, however empirical work is still in its early stages. Some recent studies have explored how regional variations in behaviour appear to be driven by social custom (Durlauf 2004). In our analysis we investigate a type of neighbourhood effect by including the average regional best practice index for the region a country belongs to; and we exclude the score of the country in question from its regional average. By doing so, we aim to examine whether the average regional performance has a significant effect on a country's own performance. We also include dummy variables for the regions with the EU region as our base.

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supplied by state-owned enterprises (SOE) as a share of total investment. Where there are few SOEs and government investment is less than 15%, countries are given a rating of 10. At the opposite extreme, countries are given a rating of 0 if the economy is dominated by SOEs and government investment is more than 50%. More information is available from http://www.freetheworld.com/release.html

[9] See http://www.transparency.org/policy_research/surveys_indices/cpi for more information.

[10] Information from Gilardi (2008) is supplemented with information from regulators' websites.

3 Methodology and Results

As our dependent variable is limited, we have chosen to use an ordered logistic regression model. Our dependent variable, best practice index (*bpi)*, can be ordered such that lower index scores correspond to lower levels of best practice and higher index scores to higher levels of best practice in electricity network regulation. Ordered logistic regression is a type of ordinal regression model (ORM). For one independent variable, the model is specified as:

$$y_i^* = \alpha + \beta x_i + \varepsilon_i$$

where i is the observation and ε is a random error. The measurement model used for binary dependent variables is expanded to divide y_i^* (the latent variable) into J ordinal categories:

$y_i = m$ if $T_{m-1} \leq y_i^* < T_m$ for $m = 1$ to J

where the cutpoints T_1 through T_{J-1} are estimated. From this, we can compute predicted probabilities of observed outcomes, i.e. belonging to a category in the best practice index, for given values of x. The probability of observing $y = m$ for given values of *x*s is the region of the distribution where the latent variable y_i^* falls between cutpoints T_{m-1} and T_m:

$$\Pr(y = m \mid x) = \Pr(T_{m-1} \leq y_i^* < T_m \mid x)$$[11]

Due to the nature of our study, the number of observations is relatively small and so our analysis has some limitations. In interpreting the results of our regression models, however, we are looking for indications of interesting relationships rather than a definitive explanation of best practice outcomes.

The most interesting regressions are summarised in *Table 2*. We report the likelihood ratio chi-square and corresponding p-value which tell us whether our models as a whole are statistically significant. We also report the pseudo-R^2. There is no direct equivalent of the R^2 from OLS regression but this is one version for non-linear models. We report whether the parallel regression assumption has been violated in each of the models. This assumption states that the value of the coefficients does not depend on the value of *m*, i.e. the outcome category of the dependent variable.

For each of the independent variables, we report standardised coefficients so that we can interpret the marginal change in our best practice index variable. A one unit increase in each independent variable leads to a change in y* in terms of standard deviations, holding all other variables constant. In our sample, the standard deviation for *bpi* is 0.86 with a minimum value of 1 and a maximum of 4.

In our first model, we look at the impact of political variables alone on best practice score. The age of the independent regulator is highly significant suggesting that the probability of having a best practice score increases as the regulator becomes more experienced over time. Surprisingly, the level of corruption does not have a significant impact.

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[11] For further details of the statistical model, see Chapter 5 of Long and Freese (2006).

Table 2: Analysing best practice outcomes

Ologit models	*1 (Political variables only)*	*2*	*3*	*4*
Dependent Variable	BPI	BPI	BPI	BPI
No. of observations	40	32	37	37
LR chi square	11.48	19.17	19.89	25.13
Prob > chi square	0.0094***	0.0077***	0.0058***	0.0015***
Pseudo R^2	0.1294	0.2513	0.2350	0.2968
Parallel regression assumption	Not Violated	Violated***	Violated***	Violated***
Independent Variables				
Number of companies *(lncomp)*		0.1782*	0.1653	0.1653*
GDP per capita *(lgdppercap)*				0.6446**
Ratio of social science to engineering grads *(soceng)*		-0.1191		
Registering property *(propreg)*		0.0080*	0.0053	0.0029
Corruption *(cpi)*	0.1065		0.0537	-0.1561
Age of independent regulator *(lagencyyears)*	0.7190***	1.1132***	1.0410***	0.9622***
Average regional index *(ari)*	0.2464			
Latin America *(la)*		-0.9924***	-0.7968*	-0.2465
Rest of Europe *(roe)*		-1.7664**	-1.9285**	-2.2779***
Australasia *(aust)*		0.4680	0.0483	0.1124

*=significant at 10%, **=significant at 5%, ***=significant at 1%, BPI = Best practice index

Note: All coefficients reported are y-standardised coefficients (standardised by the estimated standard deviation of y*) because our dependent variables is latent.

We expected to see an increase in the probability of having a high best practice score as a political system becomes less corrupt, i.e. as the *cpi* value increases.[12] In model 2, we replace the average regional index variable with regional dummy variables. The dummies for Latin America and Rest of Europe both have a significant and negative impact on best practice compared to the base (EU). This suggests that the probability of having a lower best practice score increases for countries in either

[12] It appears that the significance of *cpi* drops out once *lagencyyears* is added to the model. If we drop *lagencyyears, cpi* has a significant and positive effect on best practice as we would expect.

region compared to countries in the EU, holding all other variables constant. The size of both coefficients is also economically significant. For example in model 2, best practice score is expected to decrease by 1 standard deviation (0.86 points) for a country in Latin America compared to countries in the EU. The total number of companies in the electricity industry and the property rights indicator (*propreg)* have significant and positive impacts on best practice. Age of the regulator remains statistically and economically significant. We would expect *propreg* to have a negative coefficient because an increase in the value of this variable corresponds to a decrease in the ease of registering property. The size of the coefficient, however, is small and it becomes insignificant in subsequent models.

The variables for the total number of companies and age of the regulator are both in natural logarithmic form. Looking at model 2, for every one unit increase in the log of total number of companies, best practice score is expected to increase by 0.1782 standard deviations (0.1533 points). For every one unit increase in the log of age of the regulator, best practice score is expected to increase by 1.1132 standard deviations (0.9735 points).[13]

The significance of the number of companies and strength of property rights disappears in model 3 when we add *cpi* and drop *soceng*[14]*.* Both Latin America and Rest of Europe dummy variables remain significant and negative when *cpi* is added to the model. In our final model, however, when GDP per capita is included, Latin America is no longer significant. The Rest of Europe dummy, GDP per capita and age of the regulator are the most significant both statistically and economically in this final model. Changes in these variables appear to outweigh the importance of other regional, political and economic factors.

To illustrate the impacts of different values of the independent variables on the probability of different best practice outcomes, *Table 3* summarises the probability outcomes for four scenarios based on model 4. These scenarios look at the impact of having one standard deviation more or less than the average value for age of regulator, number of companies or per capita GDP. With average values for all independent variables, the probability of having a high best practice score is very low (0.01). Although having a large number of companies has a positive effect on best practice, the impact of lower than average GDP per capita in the second scenario outweighs this effect. In fact, the probability of a very basic best practice outcome is extremely high (0.89).

In the third scenario, there is more than a 75% chance of having a best practice score of either 2 or 3 due to the effect of a more experienced than average regulator. The chance of having a high best practice score is still low, however. In the final scenario, there is almost an 80% chance of an

[13] The maximum value in the log scale of number of companies is 6.75 (854 in the original non-transformed data). The maximum value for the logged age of the regulator is 4.47 (87 in original non-transformed data).

[14] In unreported regressions we also investigated the impact of levels of government investment and enterprises to see if this measure of privatisation has an impact on the extent of best practice, however it did not appear to have a significant effect.

intermediate or high best practice outcome. If we compare this to the 6% chance in the first scenario, we can better appreciate the impact of industry and economic variables.

Table 3: Predicted best practice outcomes

Predicted scenarios (model 4)	*Probability for outcome category*			
	VB	B	I	H
1. Average values for all independent variables	0.5821	0.3635	0.0452	0.0092
2. Larger number of companies and lower than average GDP per capita	0.8932	0.0973	0.0079	0.0015
3. Country with a well established regulator	0.1390	0.5294	0.2575	0.0742
4. Larger number of companies and higher than average GDP per capita	0.0197	0.1809	0.4079	0.3915

Note: In scenarios 2, 3 and 4, the variables mentioned are +/- one standard deviation from the average in the sample; all other independent variables are at their average values.

In three of our four models, the parallel regression assumption has been violated. Long and Freese (2006) discuss this in more detail and find that this assumption is frequently violated. They suggest considering alternative models – we have instead decided to interpret our estimates with due caution and to focus our attention mainly on the presence and direction of the effects rather than their magnitude.

4 Conclusions

Our analysis provides some initial evidence that industry size, economic and political institutions play an important role in determining best practice in electricity regulation. Due to the nature and size of our sample it would be inappropriate to offer definitive conclusions. What we can say, however, is that there is more at work than regional differences in approach.

We expected to find some evidence of a neighbourhood effect that might help to explain the dissemination of best practice methods within a particular region (e.g. to explain Austria vs Argentina). Using our average regional index variable, we did not find any evidence of this type of effect. However, there are some weak effects for particular regions and the qualitative responses to our survey suggest that this type of effect can be relevant for some countries and regions (see Haney and Pollitt (2009) for further details). The length of experience a regulator has is also an important component and the impact of this type of experience on best practice is the most consistent across our models. Higher levels of experience tend to increase the credibility of the regulator and as a result there tends to be greater capacity to adopt more complex methods (e.g. UK vs Peru).

Separating the effects of economic and political institutions is not possible due to the complex interactions between the two. Ironically, if institutions (both economic and political) have such a large role to play in determining best practice, there may be good reason for deviation from the best practice path. Rodrik's second-best institutions argument, i.e. the methods in place may in fact be more appropriate given the country context, is instructive here (Rodrik 2008). Depending on the country context it may be optimal for a country to implement some but not all best practice methods due to country-specific constraints.

Our paper is a first attempt at providing empirical evidence for the reasons behind differences in regulatory approaches in the electricity industry. It appears that the underlying reasons are inextricably linked to those that drive differences in economic development across countries. Future work would benefit from increasing the size of our country sample and its regional representativeness.

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Appendix

Table A1: Best practice index construction

ID	Indicator	Score
1	Current use of DEA, COLS, SFA[15] and/or process/activity benchmarking; 0.5 for concrete plans to use one or more of these techniques	**1, 0.5, 0**
2	Use of more than one of above benchmarking techniques in most recent price review	**1, 0**
3	Totex modelling	**1, 0**
4	Use of panel data	**1, 0**
5	Dealing with uncertainty: Full score for DEA, SFA, COLS or Process/Activity if tests for well-behaved functional form, CIA or specific adjustment	**1, 0**
6	Incorporation of environmental factors	**1, 0**
7	Use benchmarking techniques and have **either** ≥ 30 companies **or** < 30 companies and use of international data (Large dataset)	**1**
8	Mixture of both external and internal analysis = 1; Sophisticated internal analysis (i.e. using one of advanced benchmarking techniques) = 0.5; External analysis only = 0	**1, 0.5, 0**
		Max. score: 8

[15] DEA: Data Envelopment Analysis; COLS: Corrected Ordinary Least Squares; SFA: Stochastic Frontier Analysis

Table A2: Best practice scores for electricity regulation

Country	***Electricity Index score***
Austria	7
Finland	6
Belgium	5.5
Hungary; Ireland; Norway	5
Great Britain	4.5
Denmark	4
Colombia	3.25
Netherlands; Slovenia	3
Estonia	2.5
Portugal; Brazil	2.25
Argentina; Chile; New Zealand; Northern Territory; Tasmania; Venezuela	2
Bolivia; Peru	1.5
Ecuador; Panama; Poland	1
Germany; Iceland	0.5
Croatia; Cyprus; Czech Republic; Dominican Republic; El Salvador; Greece; Lithuania; Luxembourg; Mexico; Nicaragua; Romania; South Australia; Sweden; Uruguay; Western Australia	0