Electricity Market Operation: Transitioning from a Free Market to a Single Buyer structure

An econometric analysis of the Brazilian case using a Two-State Markov Switching Model

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Abstract

We examine electricity market reform in Brazil: from the 1990s till 2004 the largely hydro-powered market cleared using a market mechanism, and in March 2004 reformed to a single buyer structure. We model day-ahead returns using a Two-State Markov Switching Model with dummy variable analysis, allowing water storage and natural inflows to affect returns and volatility. Our results indicate the single buyer structure decreased volatility during stable periods but worsened energy crises. Post-reform, we find a more forgiving environment for the allocation of stored energy given natural water inflows, however sub-optimal water management leads to energy crises developing.

The debate around optimal energy market structures is one that captures the attention of regulators, retailers and generators around the world. The argument for government control centres around lessening market power to increase consumer surplus. In contrast, the argument for privatisation is based on efficiency gains leading to increased total surplus in the market. Comparing the two structures has always been problematic because it is difficult to compare a single buyer model in one country with a free market in another, while remaining confident that results aren't biased by cultural differences, geographic effects, or political influences. This article examines Brazil, which is a singular case: the Brazilian market from 1990s-2004 is a free market, while since March 2004 it has a single buyer structure. Our paper aims to evaluate the effect on electricity returns and electricity return volatility from shifting to a single buyer model, by conducting a case study of the Brazilian market reform.

Brazil is the 10th largest energy consumer globally, and generates approximately 71% of its electricity from hydropower (World Factbook (2013-14)). Due to the warm climate in Brazil, electricity use generally peaks between November and February, when it is used for cooling. The market is connected by the *Sistema Interligado Nacional* (National Interconnected System) and divided into four regions. This study uses data from the *Operador Nacional do Sistema Elétrico* (the National Grid Operator, denoted ONS). The market undergoes reform in the 1990s and in 2004. The 1990s reforms are designed to encourage private investment and increase productivity in the market, but are not as straightforward as planned primarily due to the complexity of the market (De Souza and Legey (2010)). The early 2000s see rationing of electricity due to a supply shortage from June 2001 to February 2002, which leads to further reforms to the market in March 2004. These second reforms create two seperate contracting environments for the purchase of electricity; the Free Contracting Environment (denoted FCE) and the Regulated Contracting Environment (denoted RCE). The RCE is the environment that retailers (and by extension household consumers) must contract in, and prices are set by the regulator. The FCE is used by large companies who contract directly with the generators. Our project aims to evaluate the effect on electricity prices and electricity price volatility of shifting from the conventional electricity market to the single buyer model, using data from the free market and the RCE. The RCE is comparable due to the high degree of control exercised by the regulators in price setting.

While other studies examine the 1990s reforms, as yet little work has studied the '04 reform. We use data spanning ten years after the reform, and use a Markov Switching Model for electricity returns in the market to examine the reform effect. Since electricity prices are often characterised as facing periods of extreme volatility, interspersed with quiet periods, we model two states in the market, in which we allow control variables to influence electricity returns in different ways. The flexibility of the Switching Model is attractive as it allows each state to vary in mean and volatility, and indeed allows us to shape the nature of these. Behaviour of electricity prices is characterised by high volatility, strong seasonality, mean reversion and price spikes (Le Pen and Sévi (2010)), making the modelling of these prices particularly interesting. Figure 1 shows the raw price series by region, from our dataset.

This quantitative approach complements the papers in this field, such as Rego and Parente (2013), who analyse the outcome of Brazilian electricity procurement auctions in the context of electricity generation from new and old generators, using graphical analysis and dummy variable regression analysis. Though their data spans till 2010, there is little direct emphasis on the 2004 reform effect. Santos, Haddad, and Hewings (2013) study the long-run regional effects of the tariff policy of the Brazilian electricity market, focusing on the reform process that started in the 1990s. Ramos-Real, Tovar, Iootty, de Almeida, and Pinto (2009) examine productivity of the Brazilian market, using a panel of firms between 1998–2005. Coordination of generation in subsystems is studied by Carpio and Pereira (2007). Serra (2013) discusses the theoretical impact of contract market power on the efficiency of electricity sectors. Tovar, Ramos-Real, and De Almeida (2011) analyse the effect of firm size on productivity using Brazilian data spanning till 2005.

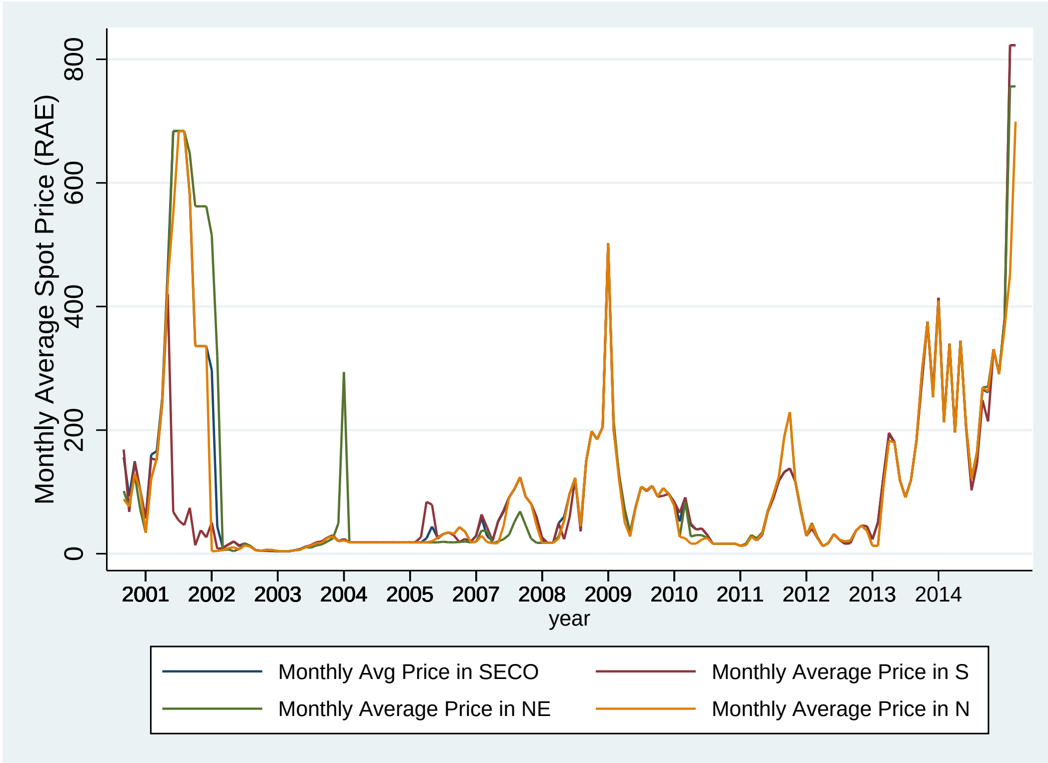

Figure 1: Spot prices by region

We find that the reform appears to decrease volatility in spot price returns in quiet periods. However, the market still spends some periods in an unstable state both pre- and post- reform. This unstable state worsens after the introduction of the RCE. We also characterise the reform by the creation of a more forgiving environment for the allocation of stored energy given levels of natural inflows, the key catalyst for entering the unstable state. However in spite of this more forgiving environment, storage management has often led to situations where prolonged energy crises could develop.

The rest of the paper is organised as follows. Section 1 outlines our methodology for the Markov Model and section 2 describes our dataset. In Section 3 we analyse the construction of our model and the key results, then Section 4 concludes.

1 Methodology

We use a Two-State Regime Switching Model with Markov chain probabilties of state persistence, to model the day-ahead returns in an electricity market. We allow each state to have seperate return and volatility equations. The allocation between states is determined by an unobserved state variable denoted s.

We use a modified Two-State Regime Switching model (see Hamilton (1989)) with normally distributed residuals. Accordingly, we model the returns as follows:

$$
\begin{aligned}
r_{t,s} &= \mu_s + \beta_s X_t + \epsilon_s \\
\epsilon_s &\sim N(0, \sigma_s^2) \\
\sigma_s &= e^{(\delta_s X_t)} \\
s &\in \{1, 2\},
\end{aligned}
$$

where r_s are the deseasonalised returns, μ_s is the intercept in the model, and X is a matrix or vector of covariates. ϵ_s represents the residuals in the return equation. Throughout the paper we will use β_s to describe coefficients in the returns equation and δ_s for coefficients in the volatility equation. s denotes the unobserved state variable.

The simplest Regime Switching Model follows a Markov Chain, where the probability that s equals some value j is dependent on the state from the previous period, as below:

$$
P(s_t = j \mid s_{t-1} = i, s_{t-2} = k, \ldots) \quad = P(s_t = j \mid s_{t-1} = i) \quad = P_{ij}.
$$

We use a Markov Switching Model in our estimation (see Hamilton (1989)). The transition probabilities are $\{p_{ij}\}_{i,j=1,2}$ in our two state case. These give us the probability that state i will be followed by state j.[1] These transition probabilities

[1]Note that $p_{i1} + p_{i2} = 1$.

are combined into the transition matrix $\mathbf{P}$.

$$\mathbf{P} = \begin{pmatrix} P_{11} & P_{21} \\ P_{12} & P_{22}. \end{pmatrix}$$

These parameters are then estimated using Maximum Likelihood Estimation. We use the method laid out by Hamilton (1994). Accordingly we maximise the following log-likelihood function for the observed data to estimate the parameters θ,

$$\mathcal{L}(\theta) = \sum_{t=1}^{T} \log f(r_t \mid X_t, \mathscr{Y}_{t-1}; \theta), \tag{1}$$

where $\mathscr{Y}_t$ denotes information avaliable at time t, and:

$$f(r_t \mid x_t, \mathscr{Y}_{t-1}; \theta) = 1'(\hat{\xi}_{t|t-1} \odot \eta_t). \tag{2}$$

where $\xi_{t|t}$ denotes the vector of conditional probabilities, inferred by the analysts knowledge of the population parameters and past observations. η_t represents the vector whose jth element is the conditional density given by 2, and the symbol $\odot$ denotes element by element multiplication. $\hat{\xi}_{t|t-1}$ is defined by:

$$\hat{\xi}_{t|t} = \frac{(\hat{\xi}_{t|t-1} \odot \eta_t)}{1'(\hat{\xi}_{t|t-1} \odot \eta_t)} \tag{3}$$

$$\hat{\xi}_{t+1|t} = \mathbf{P}.\hat{\xi}_{t|t}, \tag{4}$$

P represents the transition matrix given earlier. With a starting value $\hat{\xi}_{1|0}$ and an assumed value for the population parameter vector θ, we can use equations 3 and 4 recursively for $t = 1, 2, ..., T$ to find the values of $\hat{\xi}_{t|t}$ and $\hat{\xi}_{t+1|t}$ for each date in the sample.

We later allow covariates to affect the probability persistence in each state, specifically:

$$P_{11} = \frac{e^{(\gamma_1 X)}}{1 + e^{(\gamma_1 X)}} \tag{5}$$

$$P_{22} = \frac{e^{(\gamma_2 X)}}{1 + e^{(\gamma_2 X)}} \tag{6}$$

Throughout the paper, γ_s describes these coefficients in the state persistence equation. We use a ‘logistic transformation’ to ensure that these probabilities are bounded between zero and one. In order to further investigate the nature of this persistence in the long term, we also estimate ergodic probabilities (denoted λ_s) using the eigenvectors of these transition probabilities (see Hamilton (1994)).[2] Using these we can calculate the unconditional variance of our two-state model using the following formulae:

$$\begin{aligned} E(r) &= \lambda_1 E(r_1) + \lambda_2 E(r_2) \\ &= \lambda_1 \mu_1 + \lambda_2 \mu_2 \end{aligned}$$

$$\begin{aligned} E(r^2) &= \lambda_1 E(r_1^2) + \lambda_2 E(r_2^2) \\ &= \lambda_1 [Var(r_1) + \mu_1^2] + \lambda_2 [Var(r_2) + \mu_2^2] \\ &= \lambda_1 [\sigma_1 + \mu_1^2] + \lambda_2 [\sigma_2 + \mu_2^2] \end{aligned}$$

$$Var(r) = E(r^2) - [E(r)^2]$$

To estimate the variance covariance matrix for our parameter estimates we use the Outer Product of Gradients (denoted OPG) method, described by Greene (2008).[3]

[2] The ergodic probabilities are those eigenvectors associated with the eigenvalues equal to one.

[3] We also investigated using the ”Sandwich” Estimator as described by Davidson and MacKinnon (2004), however came to the conclusion that for our purposes the OPG estimator was satisfactory.

2 Data

We consider monthly average spot prices from the Brazilian Electricity market. The market itself is divied into four regions: South-East/Central West, South, North-East and North (denoted SECO, S, NE and N). The raw time series plots of these price series are shown in Appendix A. The analysis in this paper focuses on the data from the SECO region of Brazil, as it is the largest in size and electricity usage. [4] The dependent variable in our model is the return series, calculated as the log-difference in monthly prices. There are three independent time series variables in our data set. The first is a binary variable representing post-reform, equal to zero before March 2004 and equal to one otherwise. The second is *energia armazenada* or stored energy (denoted EAR) measured in monthly mean Mega Watts (MW). The EAR is a measure of electricity related to the volume of water stored in a reservoir or watershed. The calculation takes into account the productivity of the hydroelectric plants downstream and disregards the dead volume (regular minimal volume of the reservoir). In particular,

$$\begin{aligned} EAR(MWmed) &= \frac{1}{2,6298} * (V_i(hm^3) - Vmin(hm^3)) * (prodeq_i(MW/m^3/s) \\ &\quad + \sum_{j=1}^{m} prodeq_j(MW/m^3/s)), \end{aligned}$$

where, Vi is the volume stored in the reservoir i, $Vmin$ is the dead volume or minimal regular volume of reservoir i, *prodeqi* is the equivalent productivity of hydro plant associated with reservoir i, and *prodeqj* is the equivalent productivity of the m hydro plants downstream of reservoir i. m^3 denotes cubic metres, hm^3 denotes cubic hectometres, and s stands for second. The final control variable is *energia natural afluente* or natural hydropower (denoted ENA), also measured in monthly

[4] We include a table of results from our final model in Appendix C, should anyone wish to investigate the model fitted to other regions.

	Deseasonalised Variables			Non-Deseasonalised Variables		
	Returns	EAR $(10GW/month)$	ENA $(10GW/month)$	Returns	EAR $(10GW/month)$	ENA $(10GW/month)$
mean	0.0000	0.0298	-0.0053	0.0103	11.4852	3.2769
median	0.0274	0.9148	-0.0564	0.0000	12.0982	2.8252
std. dev.	0.4585	2.9391	0.9547	0.4743	3.5778	1.6418
min	-1.8714	-9.2194	-3.0971	-1.9129	3.3196	1.1405
max	1.1968	4.8544	3.7594	1.3370	17.4172	9.1575
skewness	-0.4619	-1.1069	0.6945	-0.4793	-0.5341	1.1327
kurtosis	4.6206	4.1170	6.3711	4.5269	2.3700	4.0763

Table 1: Summary Statistics from the SECO region dataset, where EAR denotes *energia armazenada* or stored energy and ENA denotes *energia natural afluente* or natural hydropower. Note deseasonalisation was achieved by regressing on dummies for months 1-11 and an intercept, and saving the residuals.

mean MW. The ENA is the aggregate amount of electricity that can be generated by the natural hydraulic inflow to each hydro plant in a river, not considering the interference of the upstream plants. In particular,

$$ENA(t) = \sum_{i=1}^{n}(Qnat_{(i,t)} * p_{(i)})$$

Where, i refers to a specific hydro-plant of a considered watershed, t is the time interval considered (in our case a month), *Qnat(i,t)* is the natural hydraulic inflow to plant i in period t, and *p(i)* is the average productivity of hydro plant i taking into account 65% of its maximum useful storage level and the average downstream level. We gathered this data from ONS, who collects the hydro plants technical information and calculates the equivalent productivities. The definitions were sourced from ONS (2010) and Energy (2015).

These two continuous variables are interesting in our model because, for a largely hydroelectric system such as Brazil, the level of potential energy stored in the reservoirs and the quantity of kinetic energy generated purely through rainfall are likely to have a substantial effect on electricity pricing, as they are likely to affect the supply decisions taken by generators. For our estimation ENA and EAR are scaled down by 10,000, thus giving us the monthly means measured in units of 10 Giga Watts (GW). In order to remove seasonal effects, we seperately regressed each of returns, EAR and ENA on an intercept and dummy variables for months 1-11, then saved the residuals as the deseasonalised series. Plots of these series (pre- and post-deseasonalising) are given in Appendix A. Some descriptive statistics of these series are given in Table 1. The observations begin in September 2000 and run till March 2014. The market reform to a structure similar to that of a single buyer market took place in March 2004.

3 Results

3.1 Building our model

We first estimate the model with no independent variables and simple Markov switching probabilities, then build in the dummy variable reform and then the covariates EAR and ENA in the mean, volatility and probability equations.[5] The results from this estimation are found in Table 2, with standard errors in parenthesis.

As a first step, we estimate a two-state regression without covariates (see column one). In this initial model, State 1 experiences positive drift, with log prices rising by 4.9% per month on average, and low volatility of $e^{-1.7759} = 0.1693$, indicating that returns generally vary by around 17%. This state has a probability of persisting of 0.89. State 2 experiences low negative drift of around 1.7% in log prices. Volatility is higher in this state, at $e^{-0.6527} = 0.52064$, and persistence of State 2 is more likely, with a probability of 0.96. Initially at least, the model describes a relatively good state with positive drift and low volatility, and a relatively bad state with negative drift and high volatility.

In column two we introduce the reform variable into the mean equation. The results show that, all other things remaining the same, post-reform drift tends to

[5] More in depth progression of results can be found in the Appendix.

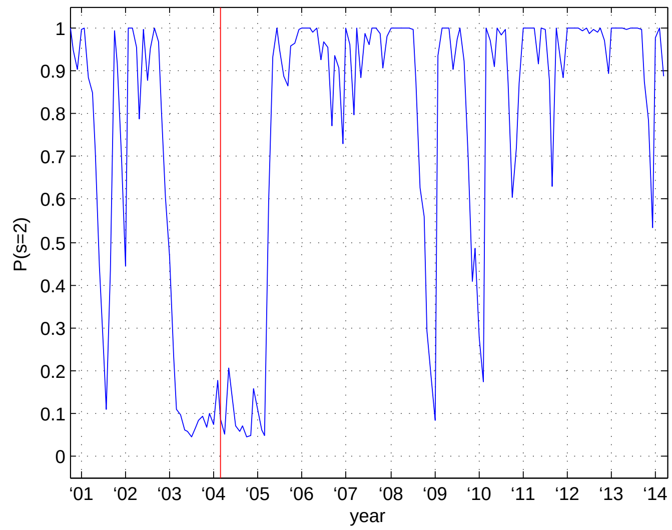

Figure 2: The probability of persisting in State 2, the more volatile state, over time, generated with only the binary variable reform (equalling one post-reform) included in the return and volatility equations. (See column 4 of table 2.)

increase (ie. prices have grown more post reform).

In column three, we also introduce EAR and ENA to the mean equation. The trend of reform increasing returns remains. As we would expect, ENA (naturally occuring hydropower from unexpected rainfall) generally has a negative effect on returns. In contrast, EAR does not appear to have a consistent effect, but rather it switches from positive to negative depending on the state. This may be due to the different decision making that occurs at high or low levels of rainfall, which is discussed further in Section 3.3.

Column 4 contains the results from including reform in the mean and volatility equations. Now that reform can also explain changes in volatility, the effect on drift alters. In one state the reform increases returns and in the other it decreases them. However, the reform appears to have had a significantly dampening effect on volatility, in both states. We also plot the probability of state persistence over time, as shown in Figure 2, with a reference line at the date of first law change for reform. The figure clearly shows that with only reform included, the series spends the majority of the time in State 2, the more volatile state.

In column 5 we see the estimated coefficients including all three covariates in

t

Progression of results from the Two State Markov Switching Model

	1		2		3		4		5		6		7	
	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se	coeff	se
μ_1	0.0490	(0.0294)	-1.6628	(0.1911)	-0.0224	(0.0869)	0.1011	(0.0486)	0.0315	(0.0832)	0.1021	(0.0428	-0.1070	(0.0746)
μ_2	-0.0172	(0.0494)	0.0258	(0.0757)	-2.0697	(2.8680)	-0.2048	(0.1632)	-0.4096	(0.2332)	-0.2903	(0.2114)	-1.6700	(750.002)
$\delta_{1\text{intercept}}$	-1.7759	(0.1539)	-1.6215	(0.6410)	-1.1781	(0.0755)	-1.6806	(0.2714)	-1.5260	(0.2788)	-1.6567	(0.2185)	-1.5256	(0.2763)
$\delta_{2\text{intercept}}$	-0.6527	(0.0659)	-0.9288	(0.0688)	-0.4145	(0.8609)	-0.4575	(0.1497)	1.2825	(0.7551)	-0.3836	(0.1747)	-1.2768	(36767)
$\gamma_{1\text{intercept}}$	0.8886	(0.0820)	0.4249	(0.2467)	0.9773	(0.0317)	0.9002	(0.0774)	0.7411	(0.1028)	2.0355	(1.1441)	9.2473	(17.005)
$\gamma_{2\text{intercept}}$	0.9600	(0.0307)	0.9599	(0.0426)	0.6619	(0.3483)	0.9661	(0.0267)	0.4140	(0.1670)	1.3200	(0.8760)	374.905	(150.752)
P0	0.0000	(1.1523)	0.0001	(2.5986)	0.0000	(3.7242)	0. 0000	(1.1513)	0.9999	(7.6862	0.0000	(1.2366)	0.0000	(564.038)
$\beta_{1\text{reform}}$			1.0063	(0.2279)	0.0623	(0.1031)	-0.1107	(0.0566)	-0.0071	(0.1180)	-0.1128	(0.0550)	0.1633	(0.0849)
$\beta_{1\text{EAR}}$					0.0425	(0.0143)			0.0607	(0.0208)			-0.0041	(0.0193)
$\beta_{1\text{ENA}}$					-0.3209	(0.0312)			-0.2749	(0.0440)			-0.2156	(0.0283)
$\beta_{2\text{reform}}$			0.0447	(0.0928)	2.7041	(3.6712)	0.2299	(0.1705)	0.4589	(0.2182)	0.3129	(0.2161)	1.5448	(750.004)
$\beta_{2\text{EAR}}$					-0.3518	(0.5836)			-0.0154	(0.0250)			0.1235	(0.0573)
$\beta_{2\text{ENA}}$					-0.0822	(0.6585)			-0.5805	(0.0459)			-0.3725	(0.0802)
$\delta_{1\text{reform}}$							-0.4312	(0.3278)	0.4331	(0.3566)	-0.4582	(0.2992)	-0.0515	(0.2834)
$\delta_{1\text{EAR}}$									-0.0672	(0.0621)			-0.0953	(0.0620)
$\delta_{1\text{ENA}}$									0.0353	(0.1195)			-0.0617	(0.1266)
$\delta_{2\text{reform}}$							-0.2747	(0.1710)	-3.3603	(0.9349)	-0.3843	(0.1899)	0.1118	(36767)
$\delta_{2\text{EAR}}$									0.6023	(0.1348)			0.0985	(0.1284)
$\delta_{2\text{ENA}}$									-0.4255	(0.3717)			-0.0366	(0.1516)
$\gamma_{1\text{reform}}$											0.4863	(1.9679)	-5.5647	(12.0504)
$\gamma_{1\text{EAR}}$													1.4154	(3.4384)
$\gamma_{1\text{ENA}}$													-8.6273	(13.7484)
$\gamma_{2\text{reform}}$											14.866	(15970)	-758.72	(42.0371)
$\gamma_{2\text{EAR}}$													445.904	(526.2325)
$\gamma_{2\text{ENA}}$													-367.48	(147.8976)

Table 2: Results: This table shows the estimated coefficients from our two state Markov switching model, where subscript 1 denotes State 1 and subscript 2 denotes State 2, with standard errors in parenthesis. β corresponds to coefficients in the return equation, δ corresponds to coefficients in the volatility equation, and γ corresponds to coefficients in the probability equation. P0 represents the initial probability of being in State 1 (the lower volatility state) at the beginning of the series. reform is a binary variable equal to one from March 2004, EAR denotes deseasonalised stored energy and ENA denotes deseasonalised natural hydropower.

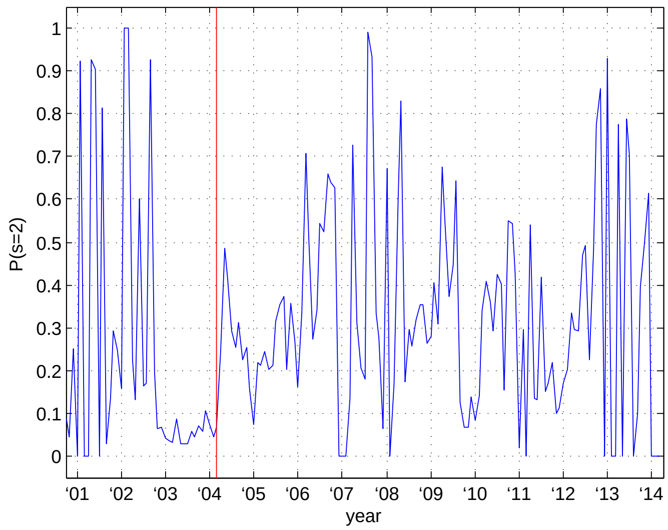

Figure 3: The probability of persisting in State 2, the more volatile state, over time, generated from the model with reform, EAR and ENA included as covariates in the return and volatility equations. (See column 5 of table 2.)

both the mean and volatility equations. The series begins in State 1, and it is the more persistent state. Pre-reform, State 1 is characterised by low positive drift and low mean volatility, and State 2 experiences high negative drift and high volatility. The series begins in State 1, and it is the more persistent state. Post-reform, we find State 1 remains relatively similar, with low positive drift and low volatility. State 2 however becomes characterised by higher positive drift and very low volatility. EAR tends to positively affect returns and volatility in one state, and negatively affect returns and volatility in the other state (perhaps counter-intuitively[6]). ENA has a consistently negative effect on returns, but not so on volatility - in one state is has a positive effect and in the other a negative effect.

We plot the probability of state persistence for this model in Figure 3. It is apparent that after the inclusion of covariates, the probability of lying in one state or another becomes less clear cut.

We next include covariates in estimated state persistence. As the states themselves change after the reforms, the persistence of each one is unlikely to be the same

[6]We experimented with various transformations of the EAR variable, looking for an intuitive relationship. In particular, we were expecting to find a negative correlation between EAR and volatility in the model. We investigated squared EAR, logged EAR, and dummy variables for different levels, however as none returned a consistently negative pair of estimated delta values, we proceed with the current variable.

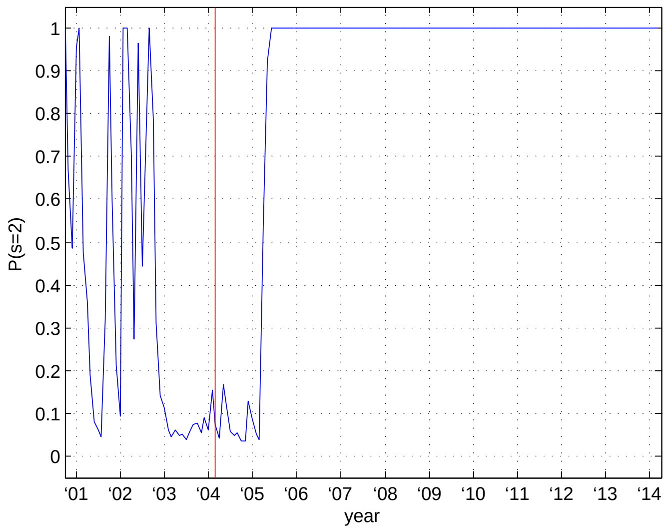

Figure 4: The probability of persisting in State 2, the more volatile state, over time, generated from the model including only the binary variable reform (0 pre reform, 1 otherwise) as a covariate in the return, volatility and probability equations.

for the whole period but rather change with the states. We include covariates in the probability equation in order to better understand the treatment effect that the reform produced.

Our first foray into more complex modelling of state persistence involves including only reform in the mean, volatility and probability equations (see column 6). From this initial estimation, we find that there continues to be a low volatility state and a high volatility state, and post reform, both of these volatilities decrease. We plot the corresponding state persistence probabilities in Figure 4. This figure paints a rather unsettling picture: from this estimation, although the reforms decreased volatilities in the good and bad states, post-reform the series appears to become effectively stuck in the high volatility state.

To further investigate this phenomenon, we used the eigenvectors of the transition matrices to find the ergodic probabilities, that is, the long term probabilities of the series being in each state. The value in row one of the following matricies is λ_1, and that in the second row is λ_2.

$$\text{ergodic probabilities}_{pre} = \begin{pmatrix} 0.6460 \\ 0.3540 \end{pmatrix}$$

$$\text{ergodic probabilities}_{post} = \begin{pmatrix} 1.2567e-06 \\ 1 \end{pmatrix}$$

As is apparent from these ergodic probabilities and Figure 4, according to this model, post-reform State 2 is an absorbing state - once in State 2 there is no transitioning back to State 1. This model does not include EAR and ENA, so this is not yet a conclusive interpretation of the outcome. For this single case, the final step included calculating the model's variance:

$$Var(r_{pre}) = 0.22308$$
$$Var(r_{post}) = 0.21525$$

The model variance for the post-reform period is lower than that of the pre-reform period.

Intuitively, the combination of EAR and ENA should affect whether the market moves to or remains in a volatile state. For this reason, in the final column we include these covariates in the probability equations as well as the mean and volatility equations. Having now built the model to its most informative structure we proceeed to analyse the treatment effect of the reform.

3.2 Results from the final case

Before the reforms, State 1 has negative drift of approximately 11% in log prices, and low mean volatility at $e^{-1.5256} = 0.2175$. 11% negative drift implies we would be expecting prices to be dropping by $1-e^{-0.11} = 0.10$ - approximately 10%. State 2 has high negative drift of 167%, (translating into an expectation of prices plummeting by $1-e^{-1.67} = 0.81$ - approximately 81%) and high mean volatility at $e^{-1.2768} = 0.27893$. These results have large standard errors, due to a paucity of State 2 observations pre reform on which to base coefficient variances. This is made clear by figure 5, in which we plot the conditional probability of being in State 2 over time. There were only two observations where P(S=2) is high pre-reform (at times 17 and 18). Naturally, the model finds estimating a variance form these observations rather daunting. Post-reform drift in State 1 increases by 16%, giving the State a mean drift of $-0.1070 + 0.1633 = 0.0563$. This can be interpreted as a low positive drift of 5.6% in log prices. In State 2, reform increases mean returns by 1.5448, giving a mean drift of -0.1252; a negative drift of 12.5%. Figure 5 also shows that post-reform, the market has spent extended periods of time in the volatile State 2. This implies that post-reform, the market was periodically volatile and experiencing negative drift.

Volatility changed post-reform: in State 1 the reform decreased mean log volatility by 0.0515, leaving a mean volatilty of $e^{-1.5256-0.0515} = 0.20657$. In State 2, on average, reform increased log volatility by 0.1118, leaving a mean volatility of $e^{-1.2768+0.1118} = 0.31192$. Thus, post-reform State 2 is still the more volatile state. EAR has a small negative effect on returns in State 1, and a larger positive effect on returns in State 2. The same relationship occurs for volatility of the model: in State 1, EAR negatively affects volatility, and in State 2 it has a positive effect. By comparison ENA has a consistently negative effect on both returns and volatility in both states.

The probability equations in this case also yield interesting results. The gamma coefficients tell us what increases and decreases the likelihood of persisting in one or other of the states. In State 1, we see that the reform decreases state persistence, EAR increases state persistence, and ENA decreases it. These estimates are all within the common scale of the previous coefficients. However, State 2 produces quite a different picture. While the direction of the effects are the same in State 2, the γ coefficents lie within |300 to 800|, much higher in absolute value than the previous state. This translates into either a very high likelihood of State 2 persisting, or a very low likelihood of State 2 persisting, depending on the values of EAR and ENA. [7]

[7] To further investigate the high values that γ takes, we performed log-likelihood ratio tests on

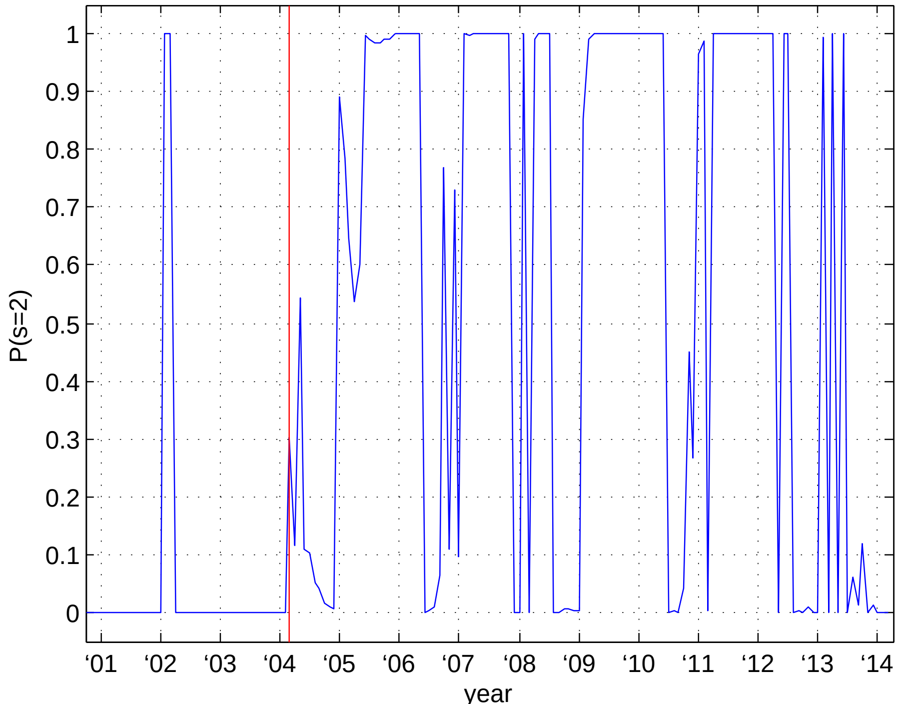

Figure 5: Probability of persisting in State 2 (the volatile state) over time from the final model, in which we include the binary variable reform, EAR (the deseasonalised stored energy), and ENA (the deseasonalised natural hydropower) in all three equations - return, volatility and state persistence. The vertical red line represents the reform.

In summary, pre-reform State 1 was characterised by low negative drift and low volatility, and State 2 by high negative drift and high volatility. Post-reform, State 1 has low positive drift and low volatility, and in State 2 we find low negative drift and higher volatility. We can infer that being in State 2 is more dangerous in terms of market stability. A reasonable question to then pose is: which combinations of EAR and ENA lead to high persistence of State 2. Or put another way: when is there a risk of a prolonged energy crisis?

3.3 The EAR/ENA Effect

In this section, we discuss the effect that the EAR to ENA ratio has on the electricity market's stability. The question is at what combinations of EAR and ENA are we finding the system at risk of peristing in the volatile State 2. To answer this

these coefficients. The results are found in Appendix B.

we numerically found the combinations that set the probability of persisting in State 2 equal to $e^0/(1+e^0) = 0.5$, computed seperately pre and post reform. Were this probability to increase, the market would be in a kind of "danger zone", since if it falls out of State 1 it is likely to remain in State 2 for more than one period. We report these relationships in figure 6, where they are plotted in blue. The "safe zone" is below this line.

We also performed cointegration analysis on these covariates to analyse their behaviour in relation to one another. We perform the analysis on the pre- and post-reform periods seperately, to yield:

$$\hat{\text{EAR}}_{pre} = \underset{(0.4959)}{-2.072} + \underset{(0.5543)}{2.131}\,\text{ENA}_{pre}$$

$$\hat{\epsilon}_{\text{diff,pre}} = \underset{(0.0865)}{-0.1735}\epsilon_{\text{lag,pre}}$$

$$\hat{\text{EAR}}_{post} = \underset{(0.1480)}{1.0072} + \underset{(0.1525)}{1.0615}\text{ENA}_{post}$$

$$\hat{\epsilon}_{\text{diff,post}} = \underset{(0.0499)}{-0.0981}\epsilon_{\text{lag,post}}$$

The intercepts and coefficients on ENA in the first regressions shown above describe the ratios of EAR to ENA tending to occur in the model. The negative coefficients on ϵ_{lag} in the second lines of regression show that, both pre- and post-reform, there is mean reversion. These critical mean-reverting ratios are also plotted in figure 6, in red.

There are several key results apparent from these graphs. Firstly, from the scatter of points it is apparent that deseasonalised EAR and deseasonalised ENA are positively correlated. This makes intuitive sense: how generators react to unsea-

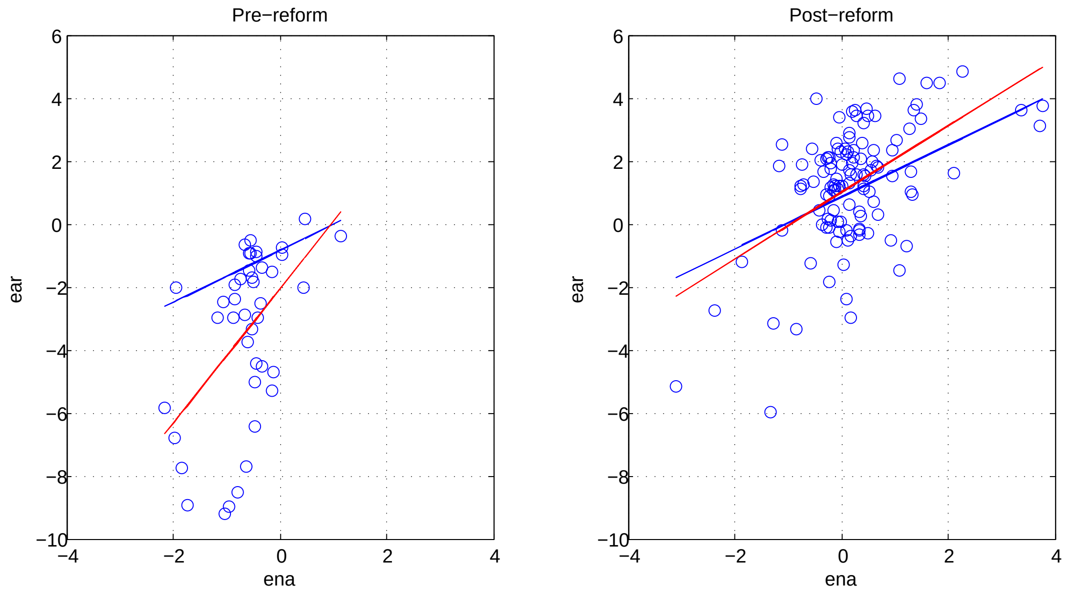

Figure 6: In these figures we see blue lines indicating the combination of deseasonalised EAR and deseasonalised ENA that will yield P22=0.5. (Below these lines we are in a safe zone.) Red lines indicate the mean reversion line given the actual coordinates from the dataset, represented by the circles.

sonal rainfall levels is likely to depend largely on how much water is already in their reservoirs or water sheds. For example, if deseasonalised ENA is low, indicating that the season is drier than would be expected, it is natural that the amount of water allowed to sit in the reservoirs (not generating electricity) would fall. This is due to the demand for electricity generation still being present, leading to the generators running reserves through the system. This would lead to a deseasonalised EAR proportionally lower than zero based on the severity or duration of the drought. In contrast, a generator could be excused for storing water during times of high rainfall. Comparing the blue lines pre- and post- reform shows that the "safe zone" has increased in size, as the line shifted up post-reform. This implies that the generators are working within a more forgiving environment - they are able to store more water in general, while running less risk of bringing about volatile electricity returns. In this sense, the reform appears to have had a positive effect.

Studying the mean reversion lines is equally interesting. The red line pre reform is significantly steeper. If we were able to infer this relationship held at all levels of ENA, this would imply that the market players pre regulation tended to react strongly to unseasonal rainfall levels - lower than usual rain would prompt less hoarding of water, and higher rain would be utilised by more hoarding taking place. However we must note that we cannot see how the free market performed in times of high deseasonalised ENA. As such, it is difficult to draw robust conclusions on how the market would have behaved in times of high rainfall.

Comparing the full graphs pre and post reform shows that though the safe zone became larger, the mean reversion of control variables post-reform does not not always fall in this zone. Pre reform, we see that for low levels of ENA, EAR is generally safely allocated well below the danger line. It is important to recall here that State 2 pre reform is based on only two observations, meaning it is unlikely to be conclusive. We must also wonder as to why the market experienced soaring prices and a shortage of supply given that this was the case. [8] Post reform, the mean reversion line is relatively closer to the danger line. In times of high rainfall after regulation, the allocation of EAR was often rather too high - leading to $P22 > 0.5$. This indicates that while the capacity to increase EAR without becoming at risk of falling into State 2 increased, the management of unseasonal EAR as a ratio to unseasonal ENA has perhaps not been as successful post-reform.

In figure 7 we see the probabilities of persisting in State 1 or 2 over time. Pre reform, P22 iss high for one month at t=18, for 2 months at t=29-30, and for 4 months between t=32-36. We know that at time 17 & 18, the conditional probability of being in state 2 iss high. Without more data is is difficult to draw more conclusions from this period. Post-reform, the system seems to have spent long periods of time at risk of persisting in State 2 should it fall out of State 1, shown by the prolonged periods at P(22)=1 in figure 7. As such, though the volatility of State 1 decreased post reform, the risk of a prolonged period of time spent in State 2 is greater.

[8] Recall that the reforms were implemented partially in response to the rationing that occured between June 2001 and February 2002.

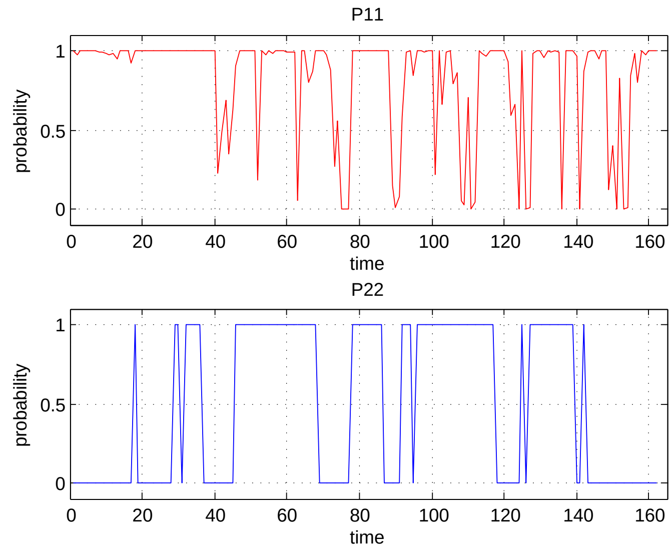

Figure 7: Probabilities of state persistence over time, for the final case, where we include all three covariates (the binary variable reform - equalling one after March 2004, EAR - the deseasonalised stored energy measure, and ENA - the deseasonalised natural hydropower measure) in all three equations - return, volatility and probability. State 1 is the more preferable state, with lower volatility.

4 Conclusion

We find that between September 2000 and February 2004, the South-Eastern/Central Western region of the Brazilian electricity market was characterised by low negative drift and low volatility in electricity returns. However there were high prices during 2001, corresponding to electricity rationing between June 2001 to February 2002. This led to the market reform in March 2004, and the creation of the RCE. The reformed market is comparable to a single buyer market due to the degree of control in the hands of the regulators.

Post-reform, the market is characterised by two states. State 1 experiences low positive drift in log prices and low volatility in returns. Volatility improves from the pre-reform period to this state post-reform. In State 2, we find low negative drift and higher volatility. In this state, volatility increases post-reform. The system switches between these states often, and spends some prolonged periods in State 2, which we characterise as energy “crises”.

Furthermore we find that the combination of deseasonalised EAR to deseasonalised ENA is instrumental in the transition between states. In particular, the ratio of EAR to ENA is a key determinant of the likelihood of persisting in the crisis state, should the series fall into it. The reform allows generators more freedom in allocating EAR given levels of ENA. However, the allocation of EAR to ENA appears to be outside the safe zone regardless of this, leading to prolonged crises.

Possible future work could involve similar econometric analysis, but including the entirety of the Brazilian electricity market, taking into account all four regions and allowing them to interact.

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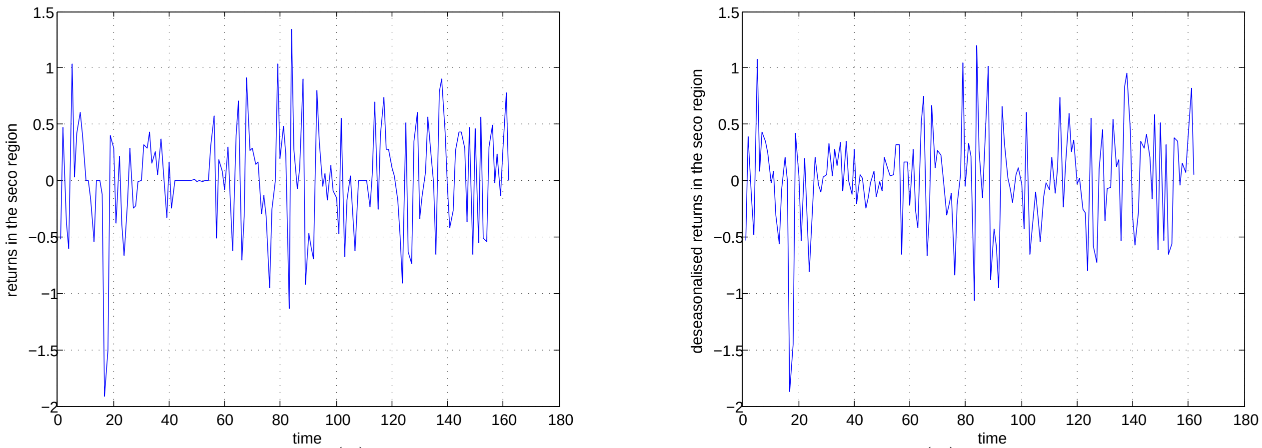
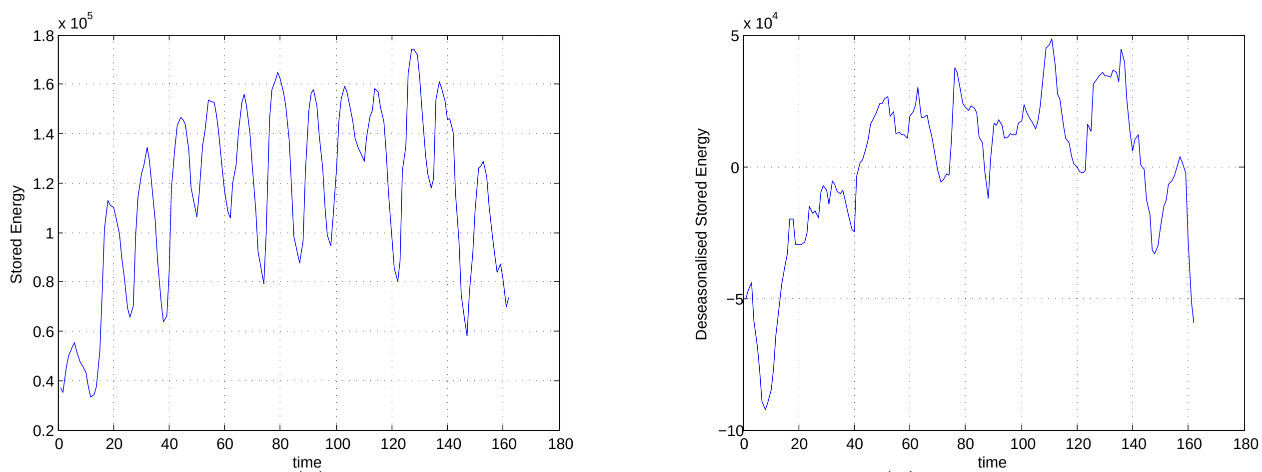
5 Appendix

A Plots and Correlations



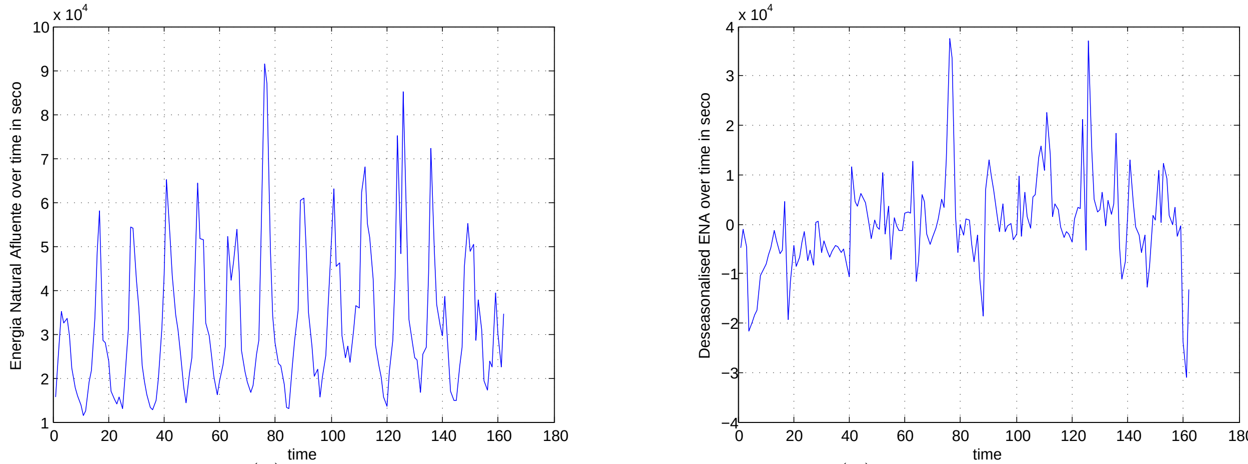
(a) returns (b) deseasonalised returns

Figure 8: return series in the SECO region



(a) stored energy (b) deseasonalised stored energy

Figure 9: stored energy series in the SECO region



(a) natural hydropower (b) deseasonalised natural hydropower

Figure 10: natural hydropower series in the SECO region

Correlations	
corr(r,EAR)	-0.054367
corr(r^2,EAR)	-0.021051
corr(r,ENA)	-0.43393
corr(r^2,ENA)	-0.05723

Table 3: Correlations between deseasonalised returns or squared returns and deseasonalised EAR (stored energy) or deseasonalised ENA (natural hydropower).

B Test Results

T-test results			
coeff	estimate	se	t-stat
$\beta_{1,1}$	-0.1107	(0.0566)	-1.9561
$\beta_{1,2}$	0.2299	(0.1706)	1.3478
$\delta_{1,1}$	-0.4312	(0.3278)	-1.3154
$\delta_{1,2}$	-0.2747	(0.1710)	-1.6063

Table 4: Testing the significance of the binary control variable reform in the simple model (no other covariates included)

For our nested model, the log-likelihood test statistic is calulated as

$$D = 2ln(\text{likelihood for null model}) - 2ln(\text{likelihood for alternate model})$$

where the null is the special case of the alternative where γ_1 is restricted to a value of zero. For the case including only reform, when the restriction is that γ_1 is set to zero:

$$D = 2(85.646) - 2(84.208)$$
$$= 2.876 \sim \chi^2_{(df=1)}$$

Compared to the chi-squared critical value (for 95% confidence and 1 df) of 3.841 - we do not reject the null.

Log-$\mathcal{L}$ ratio test results		
Case	**Restriction**	**Test stat**
reform only in all three equations	$\gamma_1 = 0$	2.876
volatility contains all covariates, otherwise only reform	$\gamma_1 = 0$	4.4988
volatility contains all covariates, otherwise only reform	$\gamma_2 = 0$	0.9292

Table 5: Results from testing the significance of the gamma coefficients. (Note: critical values for the chi-squared distribution with 1df are 3.841 for 0.95 confidence and 6.635 for 0.99 confidence.)

C Further Results

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Results from the Markov Switching Model with simple probability estimation												
	Basic Model		Including reform				Incorporating EAR and ENA					
	coeff.	se	coeff.	se	coeff.	se	coeff.	se	coeff.	se	coeff.	se
μ_1	0.0490	(0.0294)	-1.6628	(0.1911)	0.1011	(0.0486)	-0.0224	(0.0869)	-0.0039	(0.0655)	0.0315	(0.0832)
μ_2	-0.0172	(0.0494)	0.0258	(0.0757)	-0.2048	(0.1632)	-2.0697	(2.8680)	-0.4202	(0.2378)	-0.4096	(0.2332)
$\delta_{1\text{intercept}}$	-1.7759	(0.1539)	-1.6215	(0.6410)	-1.6806	(0.2714)	-1.1781	(0.0755)	-1.6170	(0.2143)	-1.5260	(0.2788)
$\delta_{2\text{intercept}}$	-0.6527	(0.0659)	-0.9288	(0.0688)	-0.4575	(0.1497)	-0.4145	(0.8609)	-0.3722	(0.2335)	1.2825	(0.7551)
P11	0.8886	(0.0820)	0.4249	(0.2467)	0.9002	(0.0774)	0.9773	(0.0317)	0.9434	(0.0428)	0.7411	(0.1028)
P22	0.9600	(0.0307)	0.9599	(0.0426)	0.9661	(0.0267)	0.6619	(0.3483)	0.8273	(0.0904)	0.4140	(0.1670)
P0	0.0000	(1.1523)	0.0001	(2.5986)	0. 0000	(1.1513)	0.0000	(3.7242)	0.0000	(1.2819)	0.9999	(7.6862
$\beta_{1\text{reform}}$			1.0063	(0.2279)	-0.1107	(0.0566)	0.0623	(0.1031)	0.0600	(0.0926)	-0.0071	(0.1180)
$\beta_{1\text{ear}}$							0.0425	(0.0143)	0.0368	(0.0137)	0.0607	(0.0208)
$\beta_{1\text{ena}}$							-0.3209	(0.0312)	-0.3495	(0.0479)	-0.2749	(0.0440)
$\beta_{2\text{reform}}$			0.0447	(0.0928)	0.2299	(0.1705)	2.7041	(3.6712)	0.4559	(0.2492)	0.4589	(0.2182)
$\beta_{2\text{ear}}$							-0.3518	(0.5836)	0.0001	(0.0248)	-0.0154	(0.0250)
$\beta_{2\text{ena}}$							-0.0822	(0.6585)	-0.1771	(0.0413)	-0.5805	(0.0459)
$\delta_{1\text{reform}}$					-0.4312	(0.3278)			0.6344	(0.2332)	0.4331	(0.3566)
$\delta_{1\text{ear}}$											-0.0672	(0.0621)
$\delta_{1\text{ena}}$											0.0353	(0.1195)
$\delta_{2\text{reform}}$					-0.2747	(0.1710)			-1.4800	(0.3344)	-3.3603	(0.9349)
$\delta_{2\text{ear}}$											0.6023	(0.1348)
$\delta_{2\text{ena}}$											-0.4255	(0.3717)

Table 6: Results - probability type 1

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Markov Switching Model results with reform in the probability estimation								
	coeff.	se	coeff.	se	coeff.	se	coeff.	se
μ_1	0.1021	(0.0428	0.0112	(0.0627)	-1.6766	(3.5708)	0.0630	(0.0766)
μ_2	-0.2903	(0.2114)	-0.7378	(0.4302)	-0.0053	(0.0647)	-0.0723	(0.1772)
$\delta_{1\text{intercept}}$	-1.6567	(0.2185)	-1.6241	(0.2188)	-1.5486	(259.6)	-1.9730	(0.5850)
$\delta_{2\text{intercept}}$	-0.3836	(0.1747)	-0.4021	(0.2873)	-1.4030	(0.2988)	-0.1876	(0.2306)
$\gamma_{1\text{intercept}}$	2.0355	(1.1441)	2.4421	(1.4954)	-0.0021	(2.0363)	21.8151	(14230157)
$\gamma_{2\text{intercept}}$	1.3200	(0.8760)	1.3697	(0.9875)	3.6374	(1.9668)	3.2114	(1.3709)
P0	0.0000	(1.2366)	0.0000	(1.4585)	0.0001	(2.2030)	0.0000	(1.1826)
$\beta_1$reform	-0.1128	(0.0550)	0.0385	(0.0827)	1.6878	(3.5712)	-0.0821	(0.1215)
$\beta_1$ear			0.0372	(0.0123)			0.0337	(0.0306)
$\beta_1$ena			-0.3198	(0.0317)			-0.1371	(0.0603)
$\beta_2$reform	0.3129	(0.2161)	0.3206	(0.4484)	0.0008	(0.0719)	0.1024	(0.1811)
$\beta_2$ear			-0.1902	(0.0618)			0.0417	(0.0163)
$\beta_2$ena			0.3642	(0.1167)			-0.3278	(0.0404)
$\delta_1$reform	-0.4582	(0.2992)	0.5509	(0.2262)	0.7639	(259.6)	0.0397	(0.9461)
$\delta_1$ear					0.0194	(0.0507)	-0.0462	(0.1596)
$\delta_1$ena					-0.0279	(0.0897)	-0.2132	(0.6005)
$\delta_2$reform	-0.3843	(0.1899)	-4.6508	(1.3515)	-0.5570	(0.4126)	-0.9361	(0.2591)
$\delta_2$ear					-0.0447	(0.0772)	0.0883	(0.0346)
$\delta_2$ena					-0.1934	(0.2406)	-0.0526	(0.0896)
$\gamma_1$reform	0.4863	(1.9679)	1.3191	(1.8572)	18.2129	(135446)	-19.2603	(14230157)
$\gamma_2$reform	14.8660	(15970)	-1.9946	(2.2464)	-1.0883	(2.5118)	15.8057	(882825)
P11-pre	0.8845		0.9200		0.4995		1	
P22-pre	0.7892		0.7973		0.9744		0.96126	
P11-post	0.9257		0.9773		1		0.92789	
P22-post	1		0.3487		0.92751		1	

Table 7: Progression of results from estimation of the mean and volatility equations containing all three covariates; the dummy for reform, EAR - deseasonalised stored energy in 10GW/month and ENA - natural hydropower also measured in 10GW/month, and where the probability equations include the variable reform.

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	Markov Switching Model results with covariates in probability estimation							
	coeff.	se	coeff.	se	coeff.	se	coeff.	se
μ_1	-1.5270	(1071496)	0.1039	(0.0528)	0.0136	(0.0985)	-0.1070	(0.0746)
μ_2	-0.0759	(0.0917)	-0.3467	(0.2310)	-1.3973	(0.2409)	-1.6700	(750.002)
$\delta_{0,1}$	-9.2103	(1016945)	-1.5645	(0.2758)	-1.1470	(0.2086)	-1.5256	(0.2763)
$\delta_{0,2}$	-1.0956	(0.1093)	-0.3024	(0.3718)	1.5445	(1.6519)	-1.2768	(36767.97)
$\gamma_{0,1}$	-3.9369	(145457831776)	0.6192	(1.5812)	18618	(3826.16)	9.2473	(17.0049)
$\gamma_{0,1}$	7.0704	(8.5401)	12.3113	(24.5898)	0.0571	(2.1742)	374.905	(150.7521)
P0	1.0000	(71.6609)	0.0000	(2.5095)	0.9999	(3.0785)	0.0000	(564.0379)
$\beta_1$reform	1.2752	(1071496)	0.1502	(0.0671)	0.0038	(0.1330)	0.1633	(0.0849)
$\beta_1$ear	0.1321	(0.0562)			0.0554	(0.0230)	-0.0041	(0.0193)
$\beta_1$ena	-0.1752	(0.1179)			-0.3952	(0.0523)	-0.2156	(0.0283)
$\beta_2$reform	0.1136	(0.1134)	0.0017	(0.2387)	1.3796	(0.2086)	1.5448	(750.0043)
$\beta_2$ear	0.0382	(0.0184)			-0.1956	(0.0321)	0.1235	(0.0573)
$\beta_2$ena	-0.3676	(0.0483)			0.0562	(0.0334)	-0.3725	(0.0802)
$\delta_1$reform	7.5227	(1016945)	-0.0412	(0.3310)	-0.0023	(0.2948)	-0.0515	(0.2834)
$\delta_1$ear			0.1250	(0.0530)	0.0283	(0.0499)	-0.0953	(0.0620)
$\delta_1$ena			-0.8106	(0.1685)	0.0612	(0.0975)	-0.0617	(0.1266)
$\delta_2$reform	0.0039	(0.1270)	-1.0294	(0.5073)	-3.4498	(1.6269)	0.1118	(36767.99)
$\delta_2$ear			0.0909	(0.1049)	0.4188	(0.2777)	0.0985	(0.1284)
$\delta_2$ena			-0.0076	(0.2012)	0.8663	(0.5088)	-0.0366	(0.1516)
$\gamma_1$reform	-93.7069	(656.1142)	-0.0047	(2.1612)	-1.4570	(3.1466)	-5.5647	(12.0504)
$\gamma_1$ear	12.5501	(305617468832)	0.5408	(0.5208)	0.0064	(0.0456)	1.4154	(3.4384)
$\gamma_1$ena	-22.9525	(2003893)	-7.1223	(4.4987)			-8.6273	(13.7484)
$\gamma_2$reform	-2.9122	(5.0965)	-18.3309	(29.6405)	-10643	(807.505)	-758.721	(42.0371)
$\gamma_2$ear	1.0526	(1.6246)	-0.5575	(1.6278)	627.67	(27.5976)	445.9035	(526.2325)
$\gamma_2$ena	-5.1024	(6.5064)	27.3835	(37.7602)			-367.484	(147.8976)

Table 8: Results from the Two-State Markov Switching model with covariates (the dummy for reform, EAR - deseasonalised stored energy in 10GW/month and ENA - natural hydropower also measured in 10GW/month) included in the return, volatility, and probability equations.

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	Southeast/Central West		**South**		**Northeast**		**North**	
	coeff.	se	coeff.	se	coeff.	se	coeff.	se
μ_1	-0.1070	(0.0746)	-0.0265	(0.0638)	-0.1947	(0.0699)	0.0532	(0.0948)
μ_2	-1.6700	(750.0020)	-0.1237	(0.1735)	0.2377	(0.3192)	0.6359	(51698653)
$\delta_{0,1}$	-1.5256	(0.2763)	-1.9457	(0.4185)	-1.6954	(0.3887)	-1.0618	(0.1750)
$\delta_{0,2}$	-1.2768	(36767.97)	-0.4316	(0.1877)	0.5793	(0.2190)	1.9684	(3204781014)
$\gamma_{0,1}$	9.2473	(17.0049)	79.3862	(432727)	6.3902	(3.8557)	20.0408	(1412562055)
$\gamma_{0,1}$	374.905	(150.7521)	2.6627	(1.7236)	3.7344	(1.5886)	7.6428	(1106006310627)
P0	0.0000	(564.0379)	0.0000	(1.0677)	0.0000	(0.3832)	1.0000	(1.0922)
$\beta_1$reform	0.1633	(0.0849)	0.0568	(0.0708)	0.3373	(0.0930)	-0.0506	(0.1185)
$\beta_1$ear	-0.0041	(0.0193)	0.4152	(0.2506)	-0.1803	(0.0402)	0.1019	(0.3545)
$\beta_1$ena	-0.2156	(0.0283)	-0.2545	(0.1261)	0.1005	(0.0643)	-0.0276	(0.0276)
$\beta_2$reform	1.5448	(750.0043)	0.1036	(0.1845)	-0.4317	(0.3269)	-0.8464	(572842072)
$\beta_2$ear	0.1235	(0.0573)	-0.1662	(0.2730)	0.4790	(0.0952)	-2.6355	(2620628076)
$\beta_2$ena	-0.3725	(0.0802)	-0.1985	(0.2062)	-1.8820	(0.2048)	-0.1031	(48017128)
$\delta_1$reform	-0.0515	(0.2834)	-0.0001	(0.4327)	-0.1908	(0.4967)	0.2555	(0.2088)
$\delta_1$ear	-0.0953	(0.0620)	2.1932	(0.8323)	-0.0497	(0.2281)	0.1245	(0.6095)
$\delta_1$ena	-0.0617	(0.1266)	-0.8819	(0.4222)	-0.3453	(0.5779)	-0.1291	(0.0437)
$\delta_2$reform	0.1118	(36767.99)	-0.1804	(0.2143)	-1.7561	(0.2609)	-3.3947	(384495384)
$\delta_2$ear	0.0985	(0.1284)	0.7715	(0.3922)	0.7006	(0.1890)	-0.4143	(2983694270)
$\delta_2$ena	-0.0366	(0.1516)	-0.3729	(0.2952)	-0.7240	(0.3914)	-0.9290	(52398454)
$\gamma_1$reform	-5.5647	(12.0504)	524.552	(26.657)	-3.3838	(3.0481)	6.6030	(17155445401)
$\gamma_1$ear	1.4154	(3.4384)	2246.23	(417.45)	1.2394	(1.1726)	-1.9892	(136275736)
$\gamma_1$ena	-8.6273	(13.7484)	-1359.7	(80.439)	15.5422	(8.9365)	0.9640	(15638998)
$\gamma_2$reform	-758.721	(42.0371)	5.1060	(3.9944)	-1.9609	(1.6564)	4.3537	(98675764213)
$\gamma_2$ear	445.9035	(526.2325)	-5.2786	(8.8926)	2.1048	(0.7887)	-0.3082	(1004123522506)
$\gamma_2$ena	-367.484	(147.8976)	-3.4591	(3.0855)	-2.9944	(2.2888)	-4.0928	(124212565775)

Table 9: Results - final case by region