Dynamic conditional score models for electricity prices in Central America

Héctor Hernández

MBA thesis defense and GESG seminar

June 2015, Universidad Francisco Marroquín

MOTIVATION

- In several Central American countries electricity market has been liberalized recently. **See Table 1.**
- We would like to find an appropriate model for Central American energy prices that may help to predict energy prices. This may help to develop future energy related projects.
- We would like to understand energy prices and determine if they have cyclical movements.

Objectives

- **Compare different models for energy price volatility.**
- A) Traditional models studied:
  - normal-GARCH; t-GARCH (Engle, 1982; Bollerslev, 1986; Taylor, 1986)
- B) Recent dynamic score models studied:
  - Beta-t-EGARCH; Gamma-GED-EGARCH; EGB2-EGARCH (Harvey and Chakravarty, 2008; Harvey, 2013; Caivano and Harvey, 2014)

Highlights

- Central American electricity sector and its regulation are reviewed for Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua and Panama. **See Table 1.**
- The dataset includes unique spot electricity prices of El Salvador, Guatemala and Panama. **See Table 2 for descriptive statistics on daily return.**
- Statistical performance of normal-GARCH, t-GARCH, Beta-t-GARCH, Gamma-GED-EGARCH and EGB2-EGARCH is compared. **See Table 7.**

Highlights

- For El Salvador, **Beta-t-EGARCH** is the most effective conditional scale specification, followed by Gamma-GED-EGARCH.
- For Guatemala, **t-GARCH** is the most effective model of conditional scale, followed by Gamma-GED-EGARCH.
- For Panama, **Gamma-GED-EGARCH** is the most effective model of conditional scale, followed by t-GARCH.

Introduction

- Application of the adequate electricity price models, which control for price shifts, is very important for the countries of Guatemala, El Salvador and Panama.

Literature

- In electricity prices large jumps or falls can be observed sometimes.
- Duffie, Gray and Hoang (1998) mention that using a GARCH model for electricity price volatility, we can estimate an *integrated volatility series*; i.e. inadequate volatility formulation.
- Escribano, Pena and Villaplana (2011) use GARCH *model with time-dependent jumps* to avoid integrated volatility series. This is a first way to model electricity price volatility.

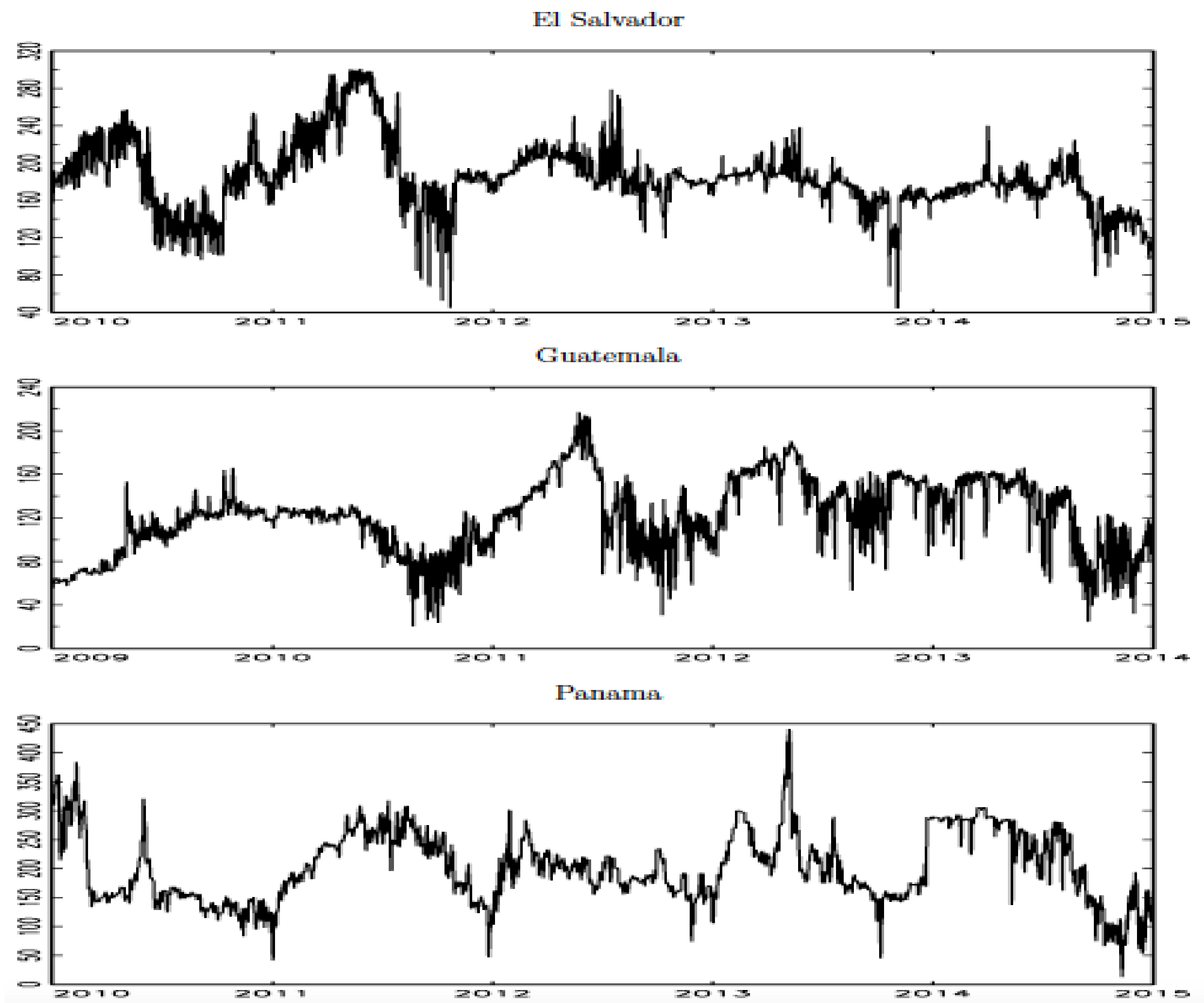
New approach

- In this work, a new approach is used based on the recent *dynamic conditional score volatility models*; introduced by Andrew Harvey (2013).
- These volatility models endogenously control for outliers, therefore, we can use dynamic conditional score models without considering a jump component in the model.
- We compare these new models with the traditional GARCH model.

Data

- Electricity price data for El Salvador and Panama:
- *1 January 2010 to 31 December 2014.*
- Electricity price data for Guatemala:
- *1 January 2009 to 31 December 2013.*
- *T*=1,826 days for all countries (same sample size for robustness)
- Unit of electricity prices: USD/MWh
- **See Table 2.**

FIGURES (energy prices)



Step 1: Control for weekly seasonality linear regression model

$$\tilde{y}_t = \delta_1 D_{\mathrm{Mo},t} + \delta_2 D_{\mathrm{Tu},t} + \delta_3 D_{\mathrm{We},t} + \\ + \delta_4 D_{\mathrm{Th},t} + \delta_5 D_{\mathrm{Fr},t} + \delta_6 D_{\mathrm{Sa},t} + \\ + \delta_7 D_{\mathrm{Su},t} + y_t$$

- OLS estimation (with heteroskedasticity and autocorrelation consistent standard errors)
- y_t is the seasonality corrected electricity return
- **See Table 3.**

Step 2: volatility models for corrected prices

MA(7)-GARCH(1,1):

$$y_t = \mu_t + \upsilon_t$$
$$\upsilon_t = \sigma_t \epsilon_t$$
$$\mu_t = \omega + \theta_1 \upsilon_{t-1} + \ldots + \theta_7 \upsilon_{t-7}$$
$$\sigma_t^2 = \alpha_0 + \beta_1 \sigma_{t-1}^2 + \alpha_1 \upsilon_{t-1}^2$$

- μ_t is MA(7) to control for the remaining weekly seasonality.
- $\varepsilon_t \sim N(0,1)$ is normal-GARCH; $\varepsilon_t \sim t(\nu)$ is t-GARCH

Step 2: volatility models for corrected prices

MA(7)-DCS(1,1) models:

$$y_t = \mu_t + v_t$$

$$v_t = \exp(\lambda_t)\epsilon_t$$

$$\mu_t = \omega + \theta_1 v_{t-1} + \ldots + \theta_7 v_{t-7}$$

$$\lambda_t = \alpha_0 + \beta_1 \lambda_{t-1} + \alpha_1 u_{t-1}$$

- μ_t is MA(7) to control for the remaining weekly seasonality. λ_t and ε_t are specified as follows for different models:

Step 2: volatility models for corrected prices

MA(7)-DCS(1,1) models:

$$\text{Beta-}t\text{-EGARCH: } u_t = \frac{(\nu+1)v_t^2}{\nu\exp(2\lambda_t)+v_t^2} - 1$$

$$\epsilon_t \sim t(\nu) \text{ i.i.d.}$$

$$\text{Gamma-GED-EGARCH: } u_t = \frac{\nu}{2}|\epsilon_t|^{\nu} - 1$$

General Error Distribution (GED)

$$\epsilon_t \sim \text{GED}(\nu) \text{ i.i.d.}$$

Step 2: volatility models for corrected prices

MA(7)-DCS(1,1) models:

$$\text{EGB2-EGARCH: } u_t = (\xi + \zeta)\frac{\epsilon_t \exp(\epsilon_t)}{1 + \exp(\epsilon_t)} - \xi\epsilon_t - 1$$

$$\epsilon_t \sim \text{EGB2}(0, 1, \xi, \zeta) \text{ i.i.d.}$$

- *Exponential Generalized Beta distribution of the second kind (EGB2)*
- **See quasi-maximum likelihood (QML) estimation results in Tables 4 to 6.**

Likelihood-based model performance

- Model quality is compared by:
- **Log-Likelihood (LL)**
- **Akaike Information Criterion (AIC)**
- **Bayesian Information Criterion (BIC)**
- **Hannan-Quinn Information Criterion (HQC)**
- The last three criteria include the value of the log-likelihood (LL) and penalize it for the number of parameters estimated.
- **See Table 7.**

Likelihood-based model performance

El Salvador	LL	AIC	BIC	HQC
GARCH-normal	2316.15	−4608.31	−4542.19	−4583.92
GARCH-t	2458.08	−4892.15	−4826.03	−4867.76
Beta-t-EGARCH	**2486.43**	**−4946.86**	**−4875.24**	**−4920.44**
Gamma-GED-EGARCH	2483.15	−4940.29	−4868.66	−4913.87
EGB2-EGARCH	2453.03	−4878.05	−4800.91	−4849.60
Guatemala	**LL**	**AIC**	**BIC**	**HQC**
GARCH-normal	1511.67	−3001.35	−2940.74	−2978.99
GARCH-t	**1770.00**	**−3516.00**	**−3449.88**	**−3491.61**
Beta-t-EGARCH	1738.79	−3451.58	−3379.95	−3425.16
Gamma-GED-EGARCH	1765.61	−3505.21	−3433.58	−3478.79
EGB2-EGARCH	1759.33	−3490.67	−3413.53	−3462.21
Panama	**LL**	**AIC**	**BIC**	**HQC**
GARCH-normal	1871.04	−3718.07	−3651.95	−3693.68
GARCH-t	2278.13	−4532.26	−4458.64	−4507.87
Beta-t-EGARCH	2266.41	−4506.82	−4435.19	−4480.40
Gamma-GED-EGARCH	**2280.67**	**−4535.34**	**−4463.71**	**−4508.92**
EGB2-EGARCH	2227.02	−4426.05	−4348.91	−4397.59

References

- Bollerslev, T. 1986 Generalized autoregressive conditional heteroskedasticity, *Journal of Econometrics*, 31, 307-327.
- Caivano, M. and Harvey, A. C. 2014 Time-series models with an EGB2 conditional distribution, *Journal of Time Series Analysis*, 35, 558-571.
- Duffie, D., Gray, S. and Hoang, P. 1998 Volatility in energy prices, in *Managing Energy Price Risk*, 2nd edn (Ed.) R. Jameson, Risk Publications, London.

References

- Engle, R. 1982 Autoregressive conditional heteroscedasticity with estimates of the variance of U.K. inflation, *Econometrica*, 50, 987-1008.
- Escribano, A., Pena, J. I. and Villaplana, P. 2011 Modelling electricity prices: international evidence, *Oxford Bulletin of Economics and Statistics*, 73, 622-650.

References

- Harvey, A. C. 2013 *Dynamic Models for Volatility and Heavy Tails*, Cambridge Books, Cambridge University Press, Cambridge.
- Harvey, A. C. and Chakravarty, T. 2008 Beta-t-(E)GARCH, Cambridge Working Papers in Economics 0840, Faculty of Economics, University of Cambridge, Cambridge.
- Taylor, S. 1986 *Modelling Financial Time Series*, Wiley, Chichester.

Thank you for your attention!