Dr. Raúl B. González Paz

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Prediction of electricity prices for Central American countries using dynamic conditional score models

SZABOLCS BLAZSEK, HECTOR HERNÁNDEZ

UNIVERSIDAD FRANCISCO MARROQUÍN, GUATEMALA

Electricity sector in Central America

Belize, Costa Rica, El Salvador, Guatemala, Honduras, Nicaragua and Panama

Well-functioning and competitive electricity market

Six Central American countries (all with the exception of Belize) are interconnected and participate in the Regional Electricity Market.

Application of adequate electricity price models is important for potential investors, market participants and regulators.

Spot electricity price data

A unique dataset of daily average spot electricity prices in USD per megawatt hours (MWh) p_t for every calendar day

For three Central American countries:

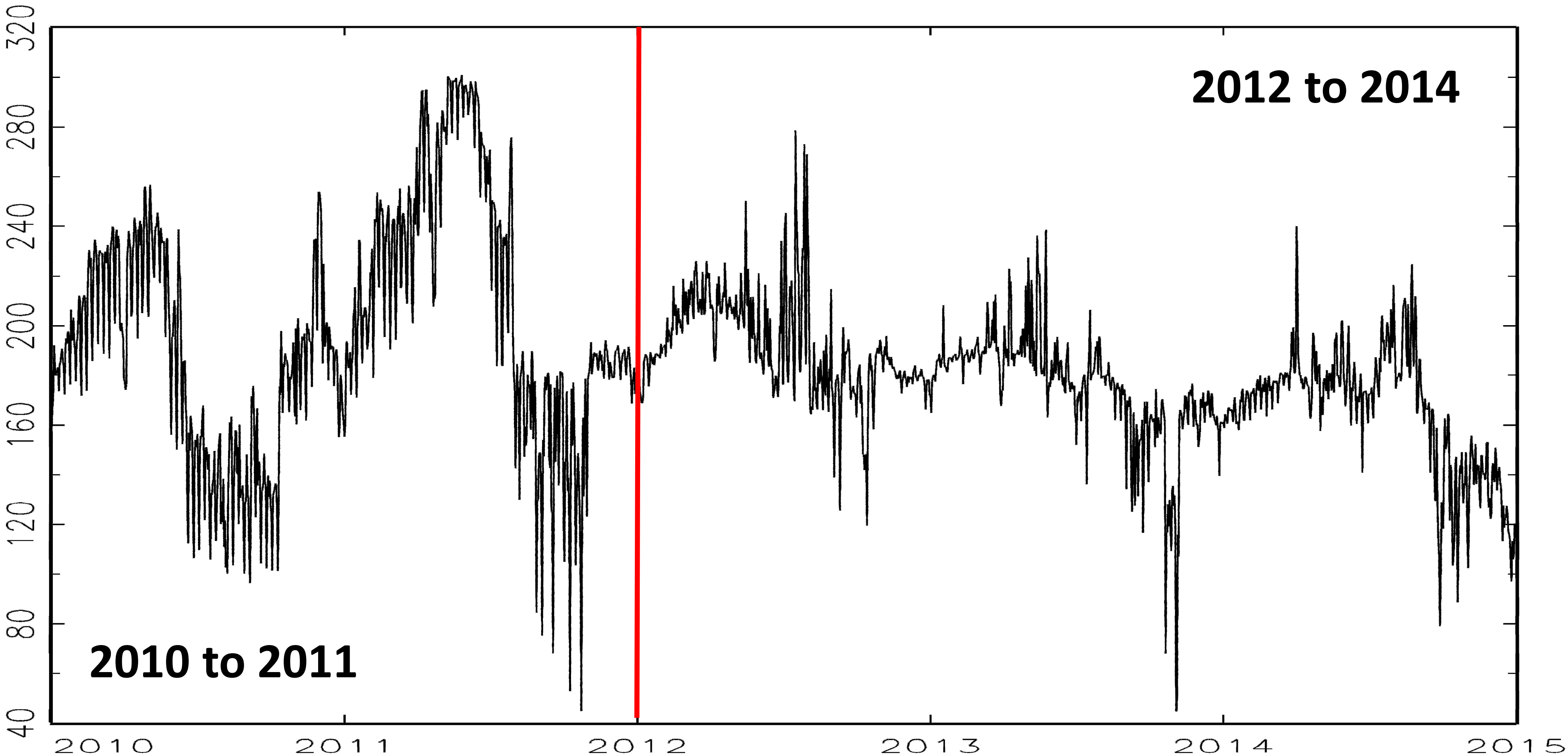
El Salvador (January 2010 to December 2014, $T = 1{,}826$)

Guatemala (January 2005 to December 2014, $T = 3{,}652$)

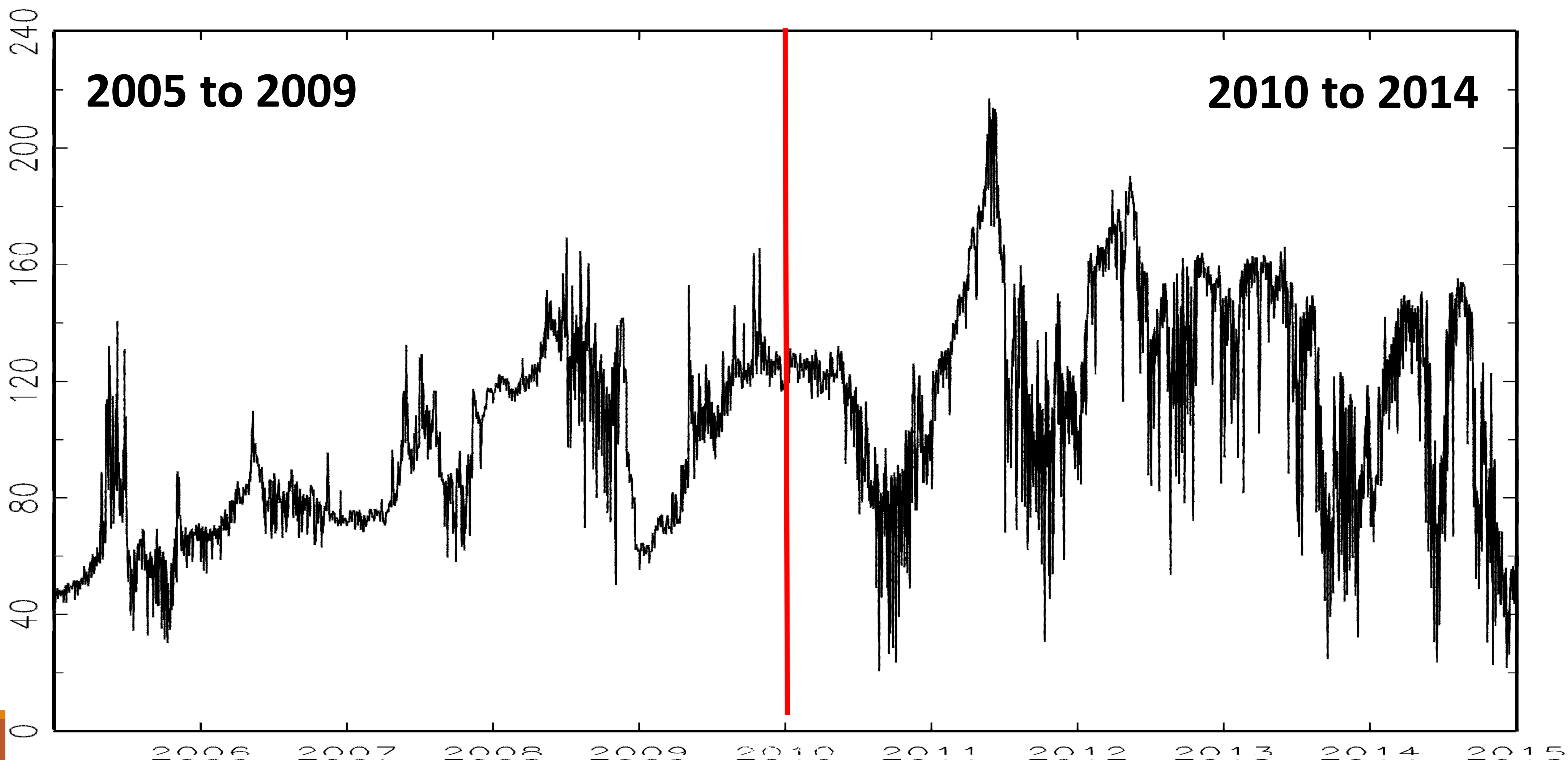
Panama (July 1998 to December 2014, $T = 6{,}028$)

(full data window)

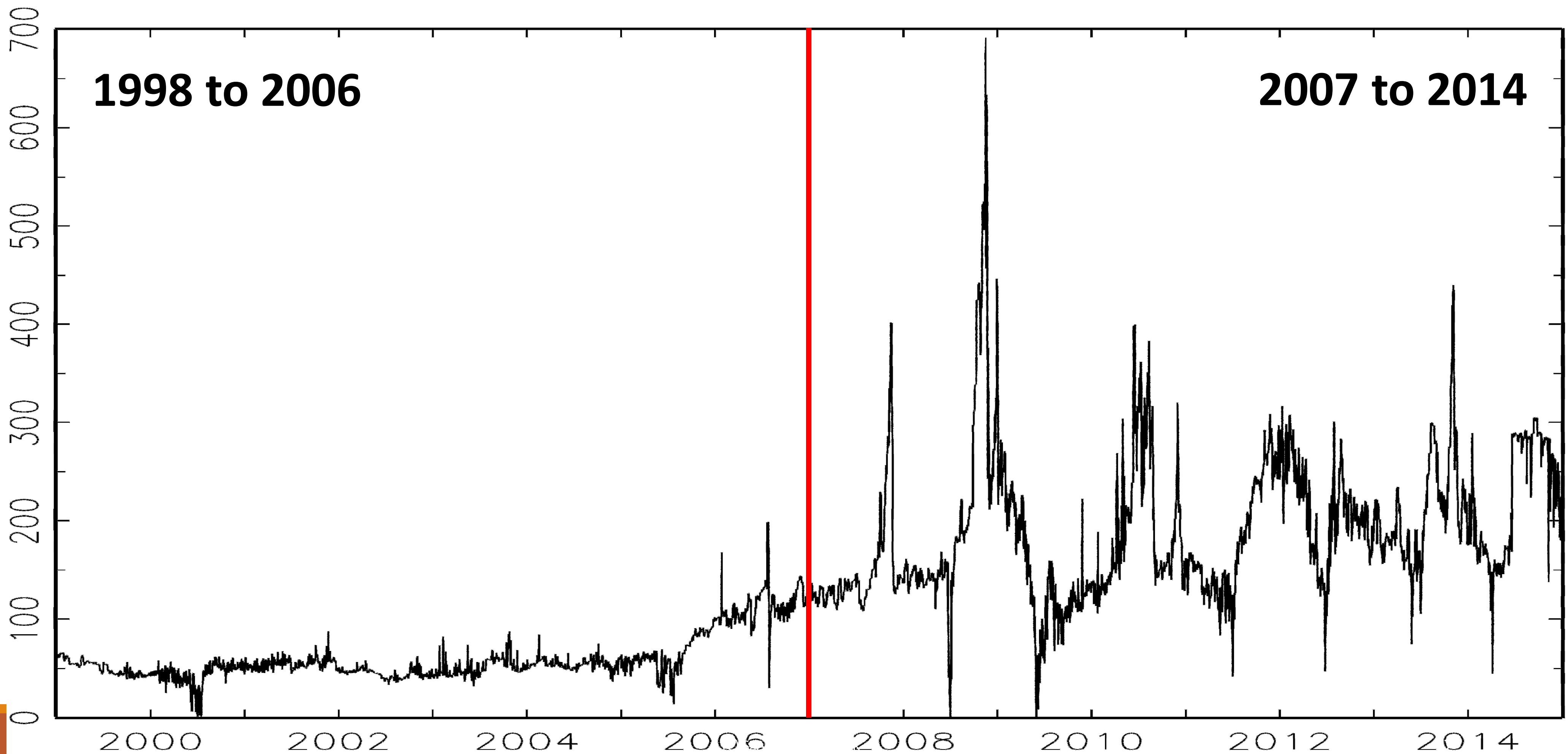
El Salvador p_t, two subperiods



Guatemala p_t, two subperiods



Panama p_t, two subperiods



Data windows for out-of-sample forecasts

For each country three **estimation windows**:

Start at the beginning of the full data window

Finish at 31th December 2011, 2012, 2013

For each country three **forecast evaluation windows**:

2012, 2013, 2014 (correspond to the estimation windows)

Properties of Central American electricity prices

(i) Mean reversion (?)

(ii) Weekly seasonal

(iii) Annual seasonal

(iv) Heteroscedasticity

Mean reversion for electricity prices

Are the Central American electricity prices mean reverting?

We do not know (a priori).

In the body of literature of electricity price models the majority of works propose mean-reverting models, but also there are works where non-mean-reverting models are used (see Escribano, Peña, Villaplana, 2011).

We formulate both I(0) and I(1) alternatives for the level of p_t.

Weekly seasonal of electricity prices

As the Central American countries are not industrialized, electricity demand decreases significantly during the weekends.

The carbon-based and geothermic baseload power plants stop on Saturday morning and restart on Sunday evening. Therefore, electricity prices attenuate during the weekend.

On Monday, demand for electricity augments. For baseload plants, about 48 hours are needed to restart a plant. Therefore, on Monday and Tuesday, electricity is generated by more expensive technologies (steam, biomass and diesel power plants), which increase prices.

Annual seasonal of electricity prices

There is an annual seasonal in electricity price time series for Central America due to

(1) significant installed capacity of hydroelectricity generation and

(2) seasonal weather-related water supply conditions

(1) Installed hydropower capacity

	Central America	
	MWh (2014)	% (2014)
Thermal power	6,714.50	49.13
Hydropower	5,721.30	41.86
Geothermal energy	625.60	4.58
Wind power	589.70	4.32
Solar power	8.40	0.06
Bioenergy	7.70	0.06
Total	13,667.20	100.00

(2) Seasonal weather-related water supply

In Central America, the water supply for hydroelectric power plants is different during the winter and summer.

The winter season in Central America is approximately from May to October or November. During the winter there is a higher water supply, and due to excess generation the prices are lower.

On the other hand, during the summer due to a lower water supply, more coal is used to generate thermal power and hence prices increase significantly.

Heteroscedasticity in electricity prices

Duffie, Gray, Hoang (1998):

GARCH may be non-stationary for electricity prices

Knittel and Roberts (2005):

EGARCH, leverage effect parameter is significant

Escribano, Peña, Villaplana (2011):

GARCH with time-varying jumps or falls

Heteroscedasticity in electricity prices

(i) We do not consider explicitly jumps or falls in the econometric framework, but replace GARCH with

Dynamic Conditional Score (DCS) volatility models.

As DCS volatility models are robust to outliers (Harvey 2013), we may obtain appropriate statistical models for electricity prices.

(ii) We consider DCS volatility models with leverage effects.

Econometric models

(1) Standard financial time series model

(2) DCS model for location, stochastic seasonal and DCS volatility

(1) Standard financial time series model

$p_t = \mu_t + s_{w,t} + s_{a,t} + v_t = \mu_t + s_{w,t} + s_{a,t} + \sqrt{\lambda_t}\varepsilon_t$

ε_t i.i.d.

Two alternatives for the level:

ARMA(1,1): $\mu_t = c + \varphi\mu_{t-1} + \theta v_{t-1}$ with $|\varphi| < 1$

RW: $\mu_t = \mu_{t-1} + \theta v_{t-1}$

(1) Standard financial time series model

$s_{w,t}$ includes weekday dummies with time-invariant parameters

$s_{a,t}$ includes month dummies with time-invariant parameters

(parameters sum to zero; parameter for the first observation is zero)

v_t is normal-GARCH (Bollerslev, 1986; Taylor, 1986) with leverage effects (Glosten, Jagannathan, Runkle, 1993)

DCS model for location and stochastic seasonal, body of literature

Harvey (2013) and Harvey and Luati (2014):

Dynamic Student-*t* location plus stochastic seasonal DCS model

Application to United Kingdom (UK) rail travel data

Log of number of kilometers travelled by UK passengers

Monthly data

DCS model for location and stochastic seasonal, our extension

We extend the dynamic Student-t location plus stochastic seasonal DCS model of Harvey (2013) and Harvey and Luati (2014), as we consider

(i) alternatives of the t-distribution for the error term ε_t

(ii) exponential DCS volatility specification

(i) Distributions of the error term

$\varepsilon_t \sim t(\nu)$ (Harvey and Chakravarty, 2008)

$\varepsilon_t \sim \mathrm{GED}(\nu)$ (General Error Distribution) (Harvey, 2013)

$\varepsilon_t \sim \mathrm{EGB2}(0,1,\xi,\zeta)$ (Exponential Generalized Beta distribution of the second kind) (Caivano and Harvey, 2014)

$\varepsilon_t \sim \text{Gen-}t(\nu,\eta)$ (Generalized-*t*) (Harvey and Lange, 2015)

(ii) Exponential DCS volatility models

Beta-*t*-EGARCH (Harvey and Chakravarty, 2008)

Gamma-GED-EGARCH (Harvey, 2013)

EGB2-EGARCH (Caivano and Harvey, 2014)

Beta-Gen-*t*-EGARCH (Harvey and Lange, 2015)

For all volatility models we measure leverage effects.

(2) DCS model for location, stochastic seasonal and exponential DCS volatility

Our DCS model for location, stochastic seasonal and DCS volatility Central American of electricity prices:

$$p_t = \mu_t + s_{w,t} + s_{a,t} + v_t = \mu_t + s_{w,t} + s_{a,t} + \exp(\lambda_t)\varepsilon_t$$

ε_t i.i.d.

Level

Two alternatives for the level:

QAR(1): $\mu_t = c + \varphi\mu_{t-1} + \theta e_{t-1}$ with $|\varphi| < 1$

RW: $\mu_t = \mu_{t-1} + \theta e_{t-1}$

We initialize μ_t by parameter μ_0 or $(1/7)\sum_{t=1}^{7} p_t$.

e_t is proportional to the conditional score with respect to μ_t:

$e_t \propto \partial \ln f(p_t | p_1, \dots, p_{t-1}) / \partial \mu_t$

Level

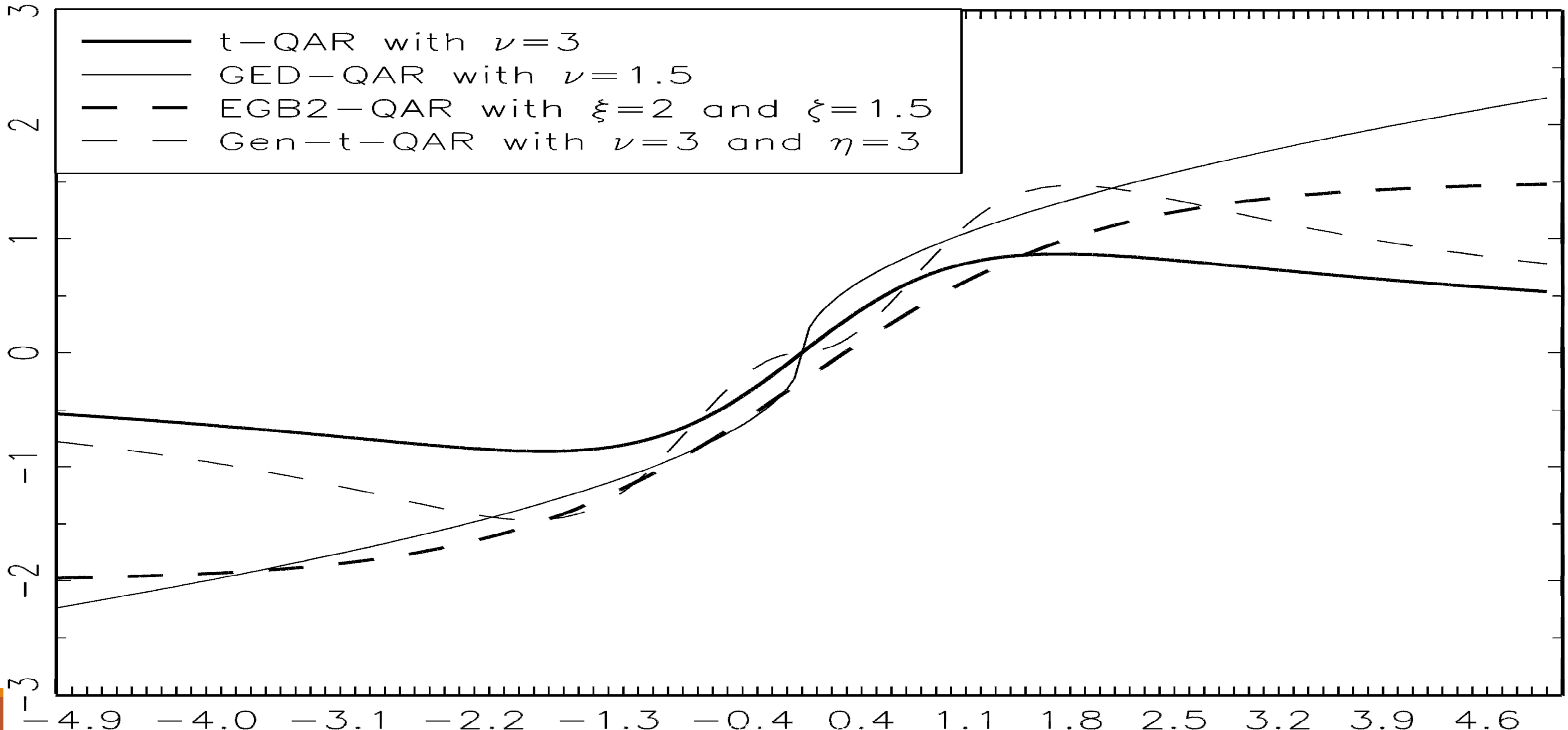
$$e_t = \left(1 + \frac{\varepsilon_t^2}{\nu}\right)^{-1} \exp(\lambda_t)\varepsilon_t \text{ for } \nu > 0,\ \varepsilon_t \sim t(\nu)$$

$$e_t = \text{sign}[\exp(\lambda_t)\varepsilon_t] \times |\varepsilon_t|^{\nu-1} \text{ for } \nu > 1,\ \varepsilon_t \sim \text{GED}(\nu)$$

$$e_t = (\xi + \zeta)\frac{\exp[\exp(\lambda_t)\varepsilon_t]}{1+\exp[\exp(\lambda_t)\varepsilon_t]} - \xi \text{ for } \xi, \zeta > 0,\ \varepsilon_t \sim \text{EGB2}(0,1,\xi,\zeta)$$

$$e_t = \frac{(\nu+1)\varepsilon_t|\varepsilon_t|^{\eta-2}}{\exp(\lambda_t)(\nu+|\varepsilon_t|^{\eta})} \text{ for } \nu, \eta > 0,\ \varepsilon_t \sim \text{Gen-}t(\nu,\eta)$$

e_t as a function of ε_t, update of the level



Weekly seasonality

$$s_{w,t} = D'_{w,t}\delta_t$$

$$D'_{w,t} = (D_{\mathrm{Mo},t}, D_{\mathrm{Tu},t}, D_{\mathrm{We},t}, D_{\mathrm{Th},t}, D_{\mathrm{Fr},t}, D_{\mathrm{Sa},t}, D_{\mathrm{Su},t})$$

$$\delta_t = \delta_{t-1} + \kappa_{w,t} e_t$$

$$\kappa'_{w,t} = (\kappa_{w,1t}, \dots, \kappa_{w,7t})$$

$$\kappa_{w,jt} = \begin{cases} \kappa_{w,j} \text{ for } D_{\mathrm{w},jt} = 1 \\ -\frac{\kappa_{w,j}}{(7-1)} \text{ for } D_{\mathrm{w},jt} = 0 \end{cases}$$

Annual seasonality

$$s_{a,t} = D'_{a,t}\gamma_t$$

$$D'_{a,t} = (D_{\mathrm{Jan},t}, \dots, D_{\mathrm{Dec},t})$$

$$\gamma_t = \gamma_{t-1} + \kappa_{a,t}e_t$$

$$\kappa'_{a,t} = (\kappa_{a,1t}, \dots, \kappa_{a,12t})$$

$$\kappa_{a,jt} = \begin{cases} \kappa_{a,j} \text{ for } D_{\mathrm{a},jt} = 1 \\ -\frac{\kappa_{a,j}}{(12-1)} \text{ for } D_{\mathrm{a},jt} = 0 \end{cases}$$

Initialize weekly and annual seasonality

We initialize the filters δ_t and γ_t by estimating a linear regression model with constant, linear time trend and all weekday and month dummies (Harvey and Luati, 2014).

We assume that the sum of all weekday parameters is zero.

We assume that the sum of all month parameters is zero.

We estimate the linear regression by using the Non-linear Least Squares (NLS) method.

The estimates of dummy parameters give δ_0 and γ_0.

Exponential DCS volatility models

$$\lambda_t = \omega + \beta\lambda_{t-1} + \alpha u_{t-1} + \alpha^* \mathrm{sign}(v_{t-1})(u_{t-1} + 1)$$

We initialize this filter by parameter λ_0.

u_t is proportional to the conditional score with respect to λ_t:

$$u_t \propto \partial \ln f(p_t | p_1, \ldots, p_{t-1}) / \partial \lambda_t$$

Exponential DCS volatility models

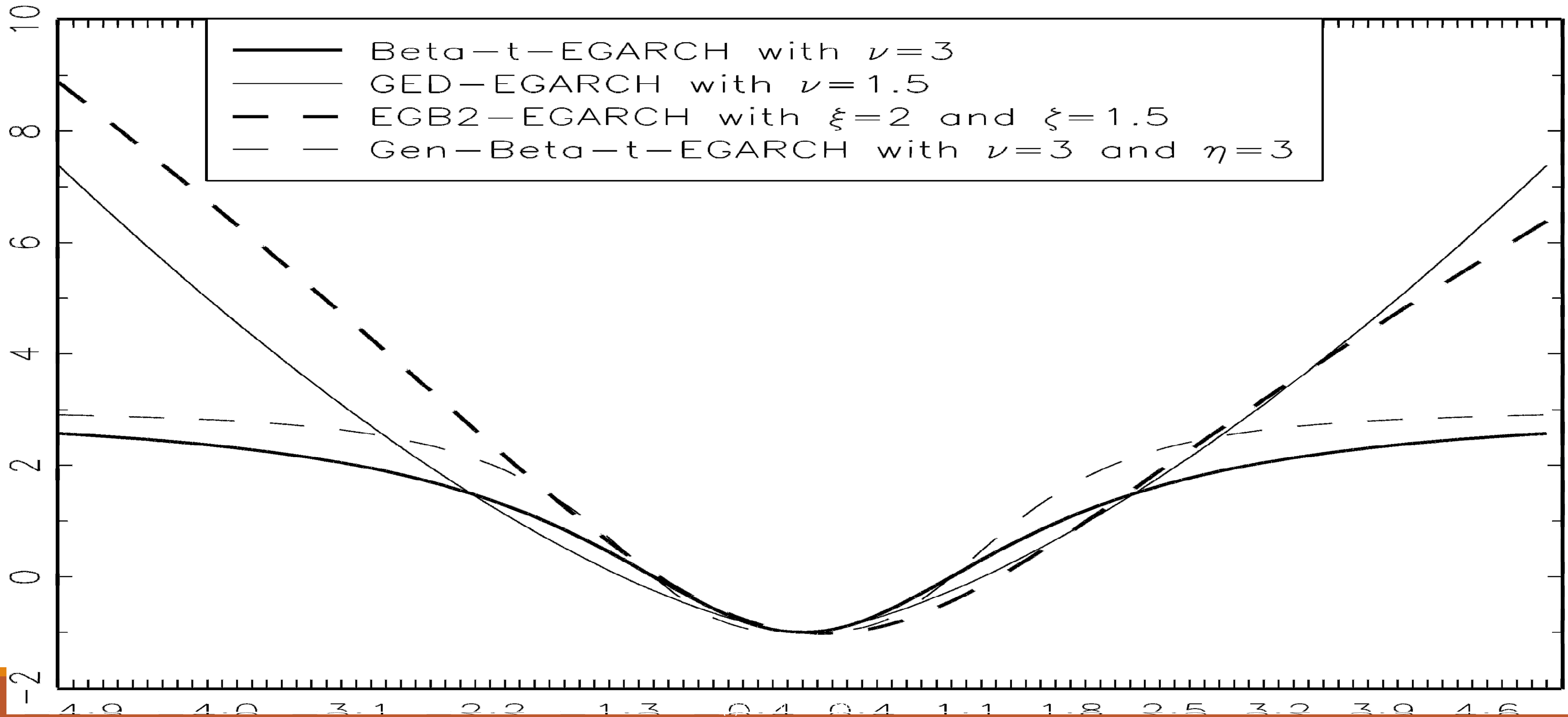
$$u_t = \frac{(\nu+1)\varepsilon_t^2}{\nu+\varepsilon_t^2} - 1 \text{ for } \nu > 0,\ \varepsilon_t \sim t(\nu)$$

$$u_t = \frac{\nu}{2} |\varepsilon_t|^{\nu} - 1 \text{ for } \nu > 1,\ \varepsilon_t \sim \mathrm{GED}(\nu)$$

$$u_t = (\xi + \zeta) \frac{\varepsilon_t \exp[\varepsilon_t]}{1+\exp[\varepsilon_t]} - \xi\varepsilon_t - 1 \text{ for } \xi, \zeta > 0,\ \varepsilon_t \sim \mathrm{EGB2}(0,1,\xi,\zeta)$$

$$u_t = \frac{(\nu+1)\ |\varepsilon_t|^{\eta}}{\nu+|\varepsilon_t|^{\eta}} - 1 \text{ for } \nu, \eta > 0,\ \varepsilon_t \sim \text{Gen-}t(\nu, \eta)$$

u_t as a function of ε_t, update of the scale



Statistical inference

Maximum Likelihood (ML) method

Robust sandwich estimator for standard errors

Delta method for transformed parameters

Start parameter values for DCS model are obtained by a preliminary four-step ML estimation procedure for $(\mu_t, s_{w,t}, s_{a,t}, \lambda_t)$.

Criterion for effective ML estimation is convergence to the maximum LL with convergence tolerance for the gradient 10^{-5}.

Statistical inference

For the standard financial time series model, the ML estimation procedure always converged effectively.

For the DCS models with $\varepsilon_t \sim t(\nu)$, the ML estimation procedure converged effectively for most of the data windows.

For the DCS models with $\varepsilon_t \sim \mathrm{GED}(\nu)$, $\varepsilon_t \sim \mathrm{EGB2}(0,1,\xi,\zeta)$ and $\varepsilon_t \sim \mathrm{Gen}\text{-}t(\nu,\eta)$, the ML estimation procedure never converged effectively. We do not report results for these DCS models.

Likelihood-based performance, El Salvador

Panel B. Mean BIC	Standard ARMA	Standard RW	DCS QAR	DCS RW
Full data window	7.8153	**7.8132**	NA	**7.6702***
First subperiod	8.0866	**8.0812**	NA	NA
Second subperiod	7.5450	**7.5383**	7.3420	**7.3320***
First estimation window	8.0866	**8.0812**	NA	NA
Second estimation window	8.0113	**8.0083**	NA	NA
Third estimation window	7.9545	**7.9542**	NA	NA

Likelihood-based performance, Guatemala

Panel B. Mean BIC	Standard ARMA	Standard RW	DCS QAR	DCS RW
Full data window	7.0469	**7.0437**	NA	**6.9991***
First subperiod	6.1875	**6.1846**	NA	**6.1021***
Second subperiod	7.8408	**7.8357**	NA	**7.7520***
First estimation window	6.5455	**6.5426**	NA	**6.4953***
Second estimation window	6.7435	**6.7400**	NA	**6.6671***
Third estimation window	6.9236	**6.9202**	NA	**6.8684***

Likelihood-based performance, Panama

Panel B. Mean BIC	Standard ARMA	Standard RW	DCS QAR	DCS RW
Full data window	**7.1087**	7.1462	NA	**6.9846***
First subperiod	5.8375	**5.8346**	**5.4638***	5.4701
Second subperiod	**8.3599**	8.3738	**8.1241***	8.1351
First estimation window	**6.7788**	6.8093	NA	**6.6291***
Second estimation window	**6.8780**	6.9046	NA	**6.7812***
Third estimation window	**6.9836**	7.0087	**6.8551***	6.8575

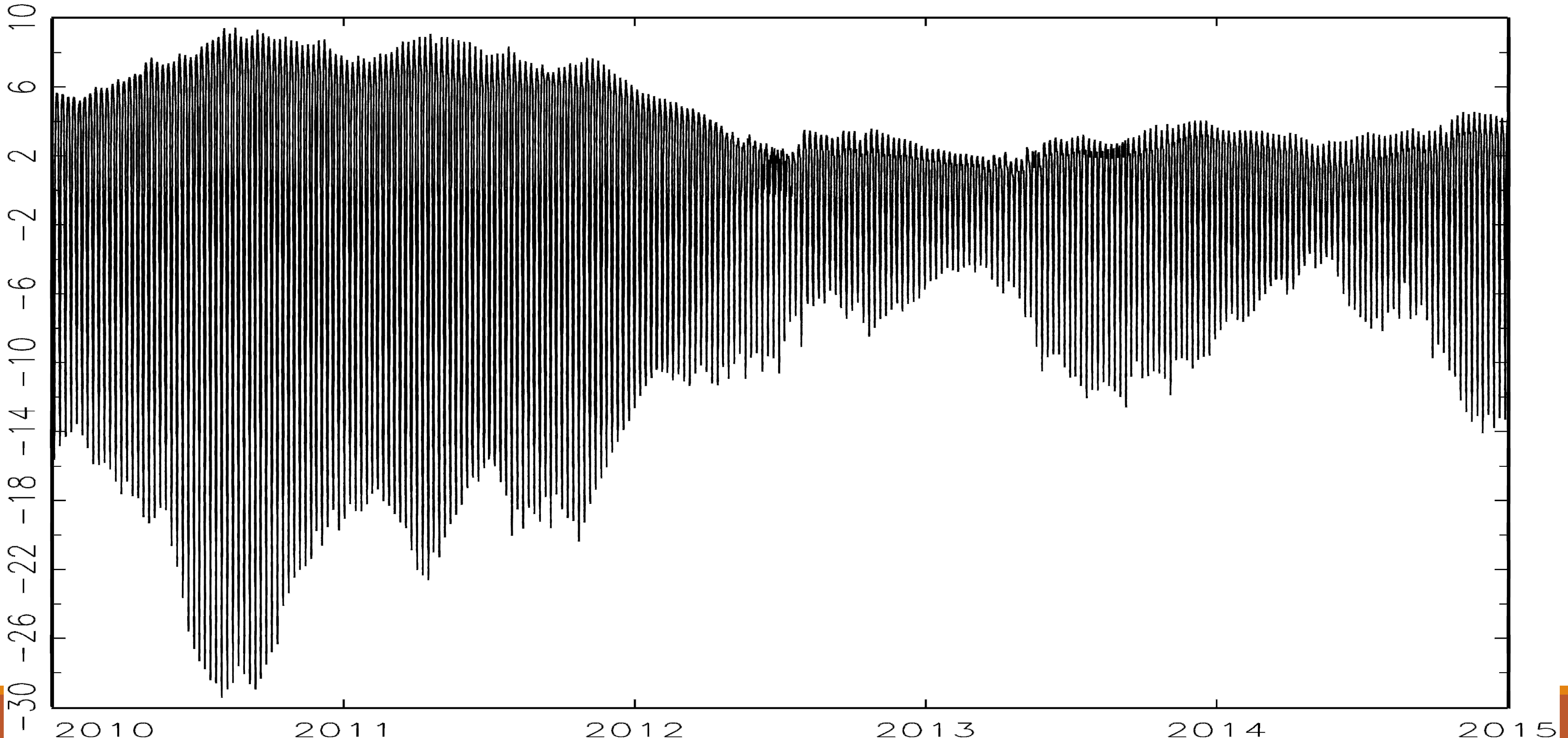
Out-of-sample point forecast performance

Panel A. Point forecasts performance			
Guatemala	RMSE, standard	RMSE, DCS	DM statistic
First forecast evaluation window	13.9273	13.7405	0.3308
Second forecast evaluation window	16.0387	15.7209	0.6213
Third forecast evaluation window	15.3719	**14.2891**	2.1019**
Panama	RMSE, standard	RMSE, DCS	DM statistic
First forecast evaluation window	16.0743	19.6480	−0.8197
Second forecast evaluation window	18.3090	20.3240	−0.3637
Third forecast evaluation window	22.8993	**21.2295**	1.8163*

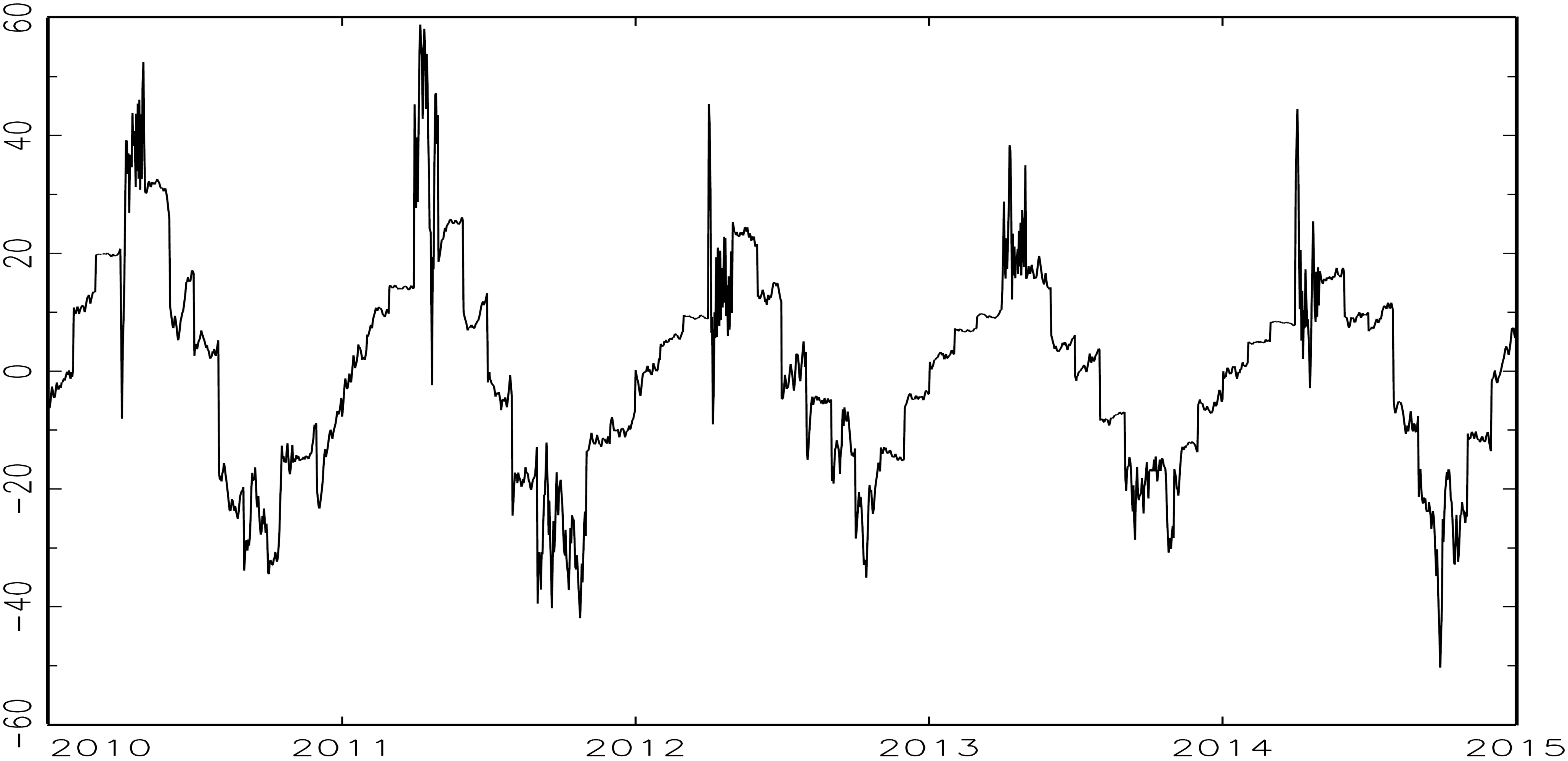
Out-of-sample density forecast performance

Panel B. Density forecast performance			
Guatemala	mean $\ln f$, standard	mean $\ln g$, DCS	AG statistic
First forecast evaluation window	-4.1043	$\mathbf{-3.8584}$	-2.2998^{**}
Second forecast evaluation window	-4.6228	$\mathbf{-4.0552}$	-2.5651^{**}
Third forecast evaluation window	-4.1009	$\mathbf{-3.9492}$	-3.0872^{***}
Panama	mean $\ln f$, standard	mean $\ln g$, DCS	AG statistic
First forecast evaluation window	-5.2971	$\mathbf{-4.1994}$	-1.9584^{*}
Second forecast evaluation window	-7.3279	$\mathbf{-4.1431}$	-2.0952^{**}
Third forecast evaluation window	-4.4754	$\mathbf{-4.2400}$	-3.9067^{***}

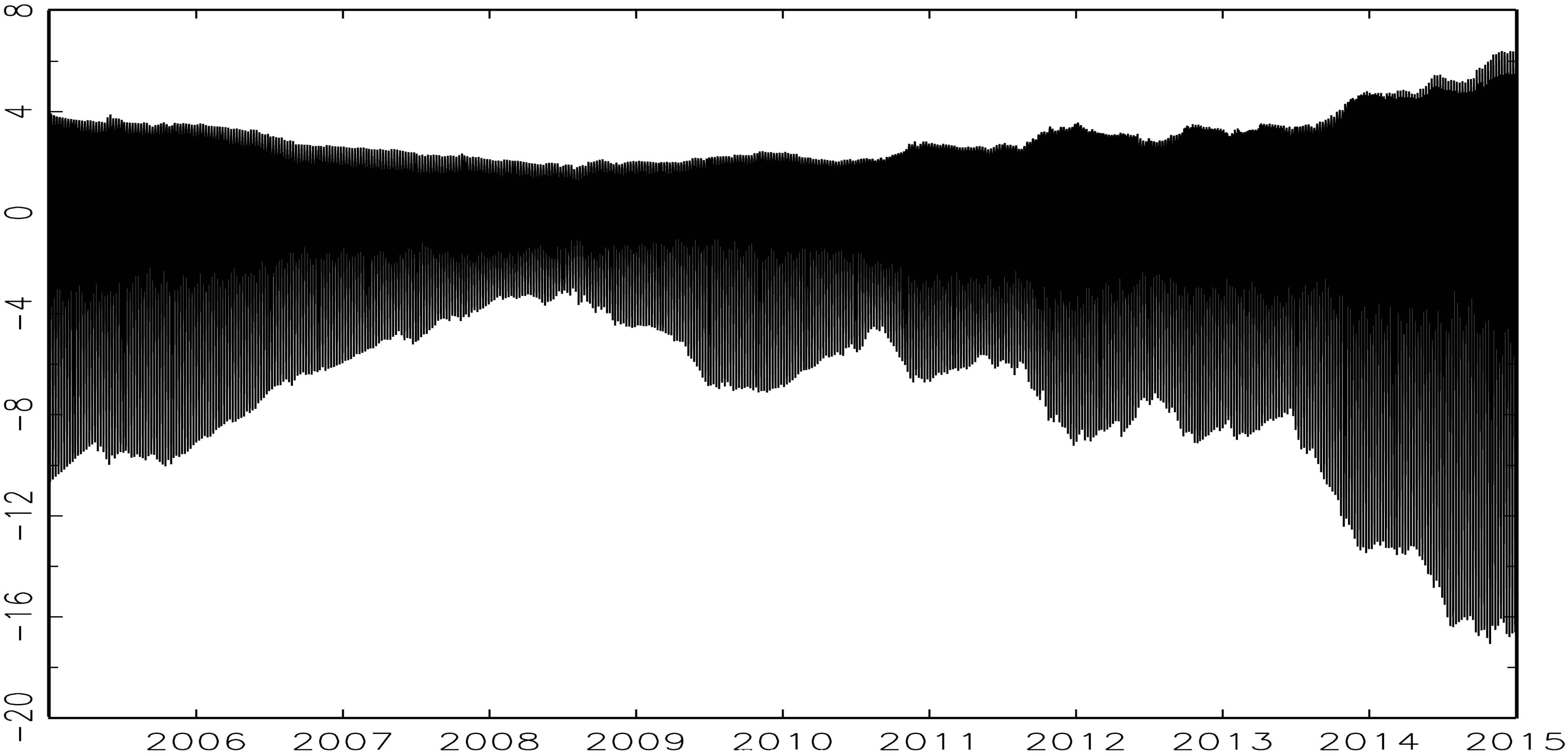
Weekly season, El Salvador, 2010 to 2014



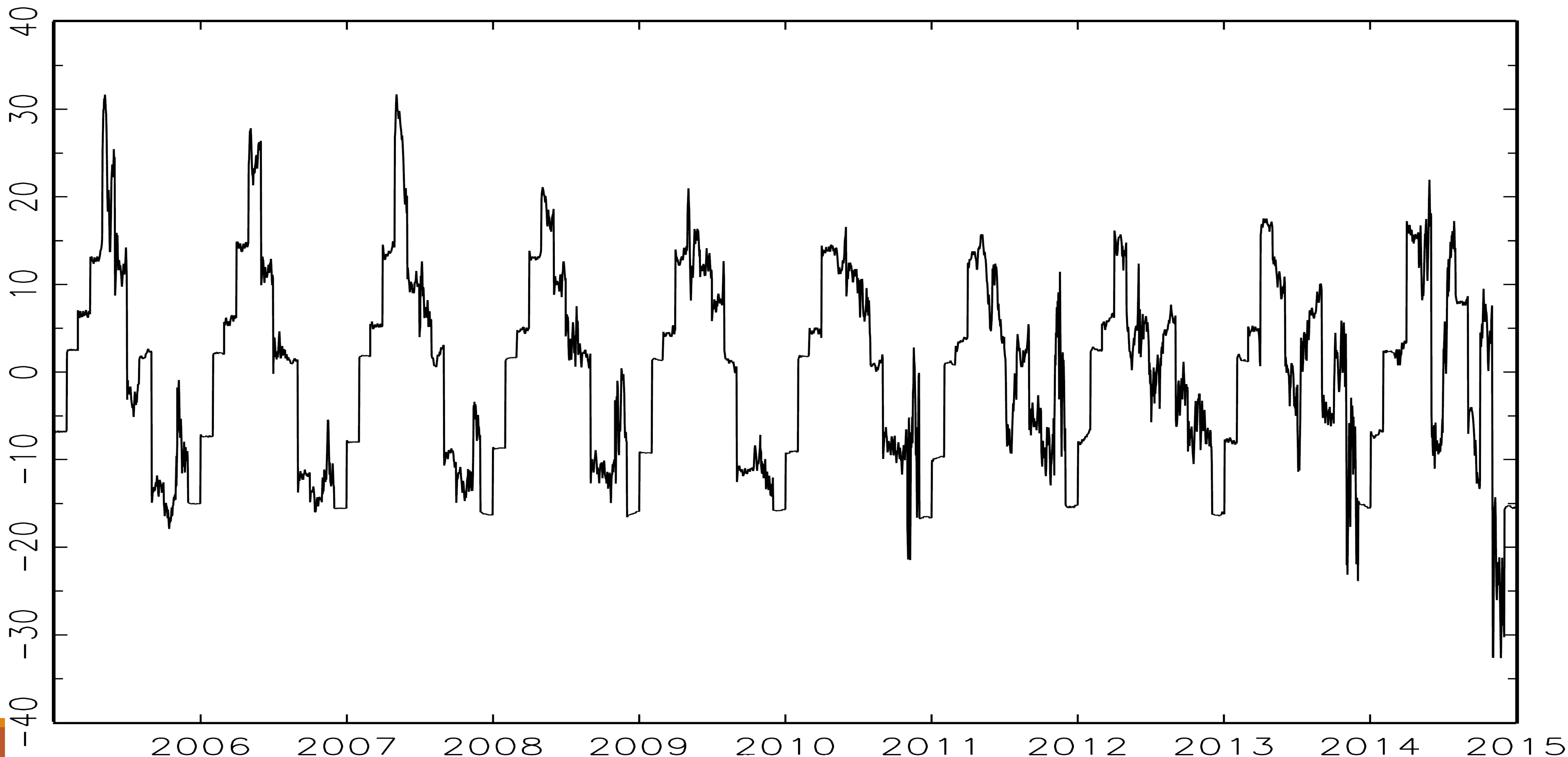
Annual season, El Salvador, 2010 to 2014



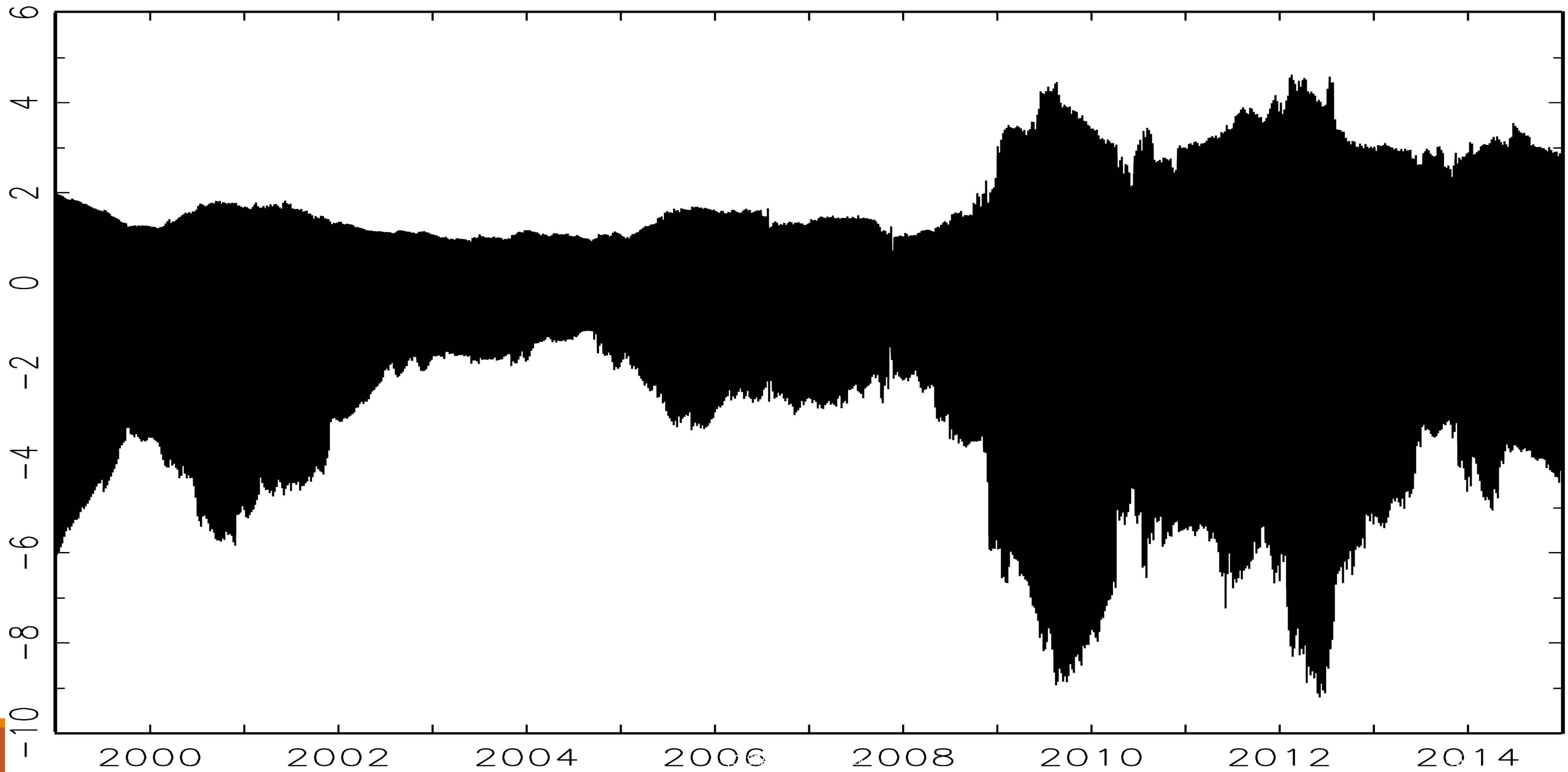
Weekly season, Guatemala, 2005 to 2014



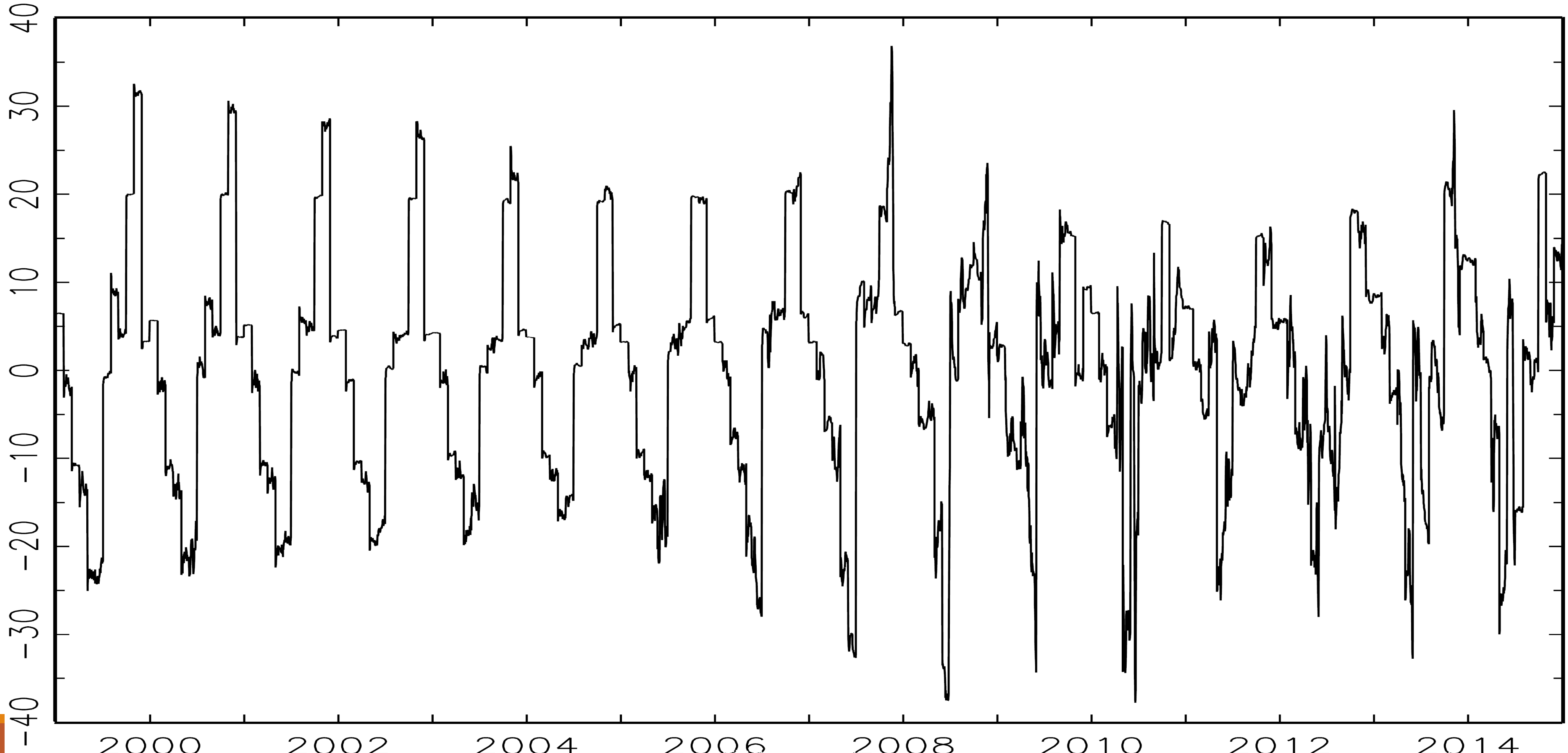
Annual season, Guatemala, 2005 to 2014



Weekly season, Panama, 1998 to 2014



Annual season, Panama, 1998 to 2014



Thank you for your attention!

SBLAZSEK@UFM.EDU