Modeling Short-run Electricity Demand with Long-term Growth Rates and Consumer Price Elasticity in Commercial and Industrial Sectors☆

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hourly peak in the work of Engle *et al.* (

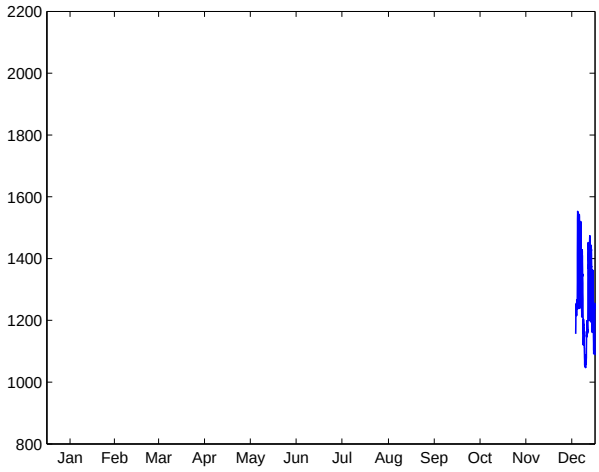
of di ering frequencies used to approximate a given functio

As most of the regressors in (are dependent on the time being forecasted predictions based on this model are simple to produce Because the short run model includes indicator variables for a base year for predictions is necessary The year variable must be within the sample period but the other calendar variables should re ect the actual year of the forecast to accurately represent when holidays and weekends occur Once a given time frame is decided pertinen

Because the diurnal load data used to estimate the short term diurnal model represents only a small subset of all commercial and industrial customers in each of the four states the diurnal load pro- les generated by model (are scaled to represent aggregate statewide consumption. This is done by comparing the total quantity demand in in the short run data sets to aggregate statewide consumption reported by the EIA. If we let A_y denote aggregate annual statewide consumption and Q_t the hourly consumption of the customer subset in the diurnal data the scaling factor for the year is given by·

$$S_y \quad \frac{A_y}{\sum_{t,} \quad Q_t} \qquad (8$$

For instance the hourly quantity demand by the subset of commercial and industrial customers in Ohio in is approximately ` p5 of the total statewide consumption thus the outputs of model (are scaled by a factor of _ 7 to forecast statewide commercial and industrial consumption. This scaling factor is applied to all of the hourly loads generated by the short term model and is included in - gure _ and all subsequent - gures.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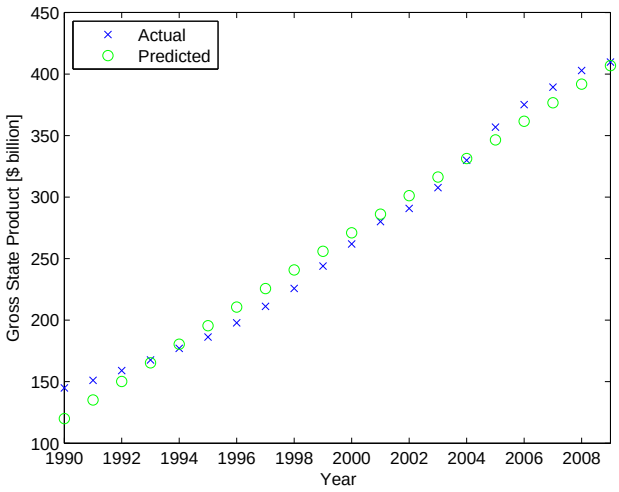

Figure · Actual and predicted values of gross state product in Virginia for the years ` _ *R* S _

Table · Regression estimates for short term models in equations (and (for Michigan. Regression *R* 's are _ p and _ 7 respectively. Model (has a D statistic of _ S

	Equation (		Equation (	
Variable	Coe- cient	*t* value	Coe- cient	*t* value
Constant	-	-	_ S	-
HD	_	_	-	-
CD	_ p	_ 7	_ 7	-
HD	-	-	-	-
CD	_	_	-	-
Day Hot	_ 7	_ l S p	(o	p S 7

Table · Regression estimates for short term models in equations (and (for Ohio. Regression R 's are - S and - respectively. Model (has a D statistic of -S

Table . Regression estimates for short term models in equations (and (for Texas. Regression R 's are . and . respectively. Model (has a D statistic of .

	Equation (		Equation (	
Variable	Coe cient	t value	Coe cient	t value
Constant	.	.	.	.
HD	.	.	.	.
CD	.	.	.	.
HD	.	.	.	.
CD	.	.	.	.
Day Hour	.	.	.	.
Day Hour	.	.	.	.
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cmBTR . Tf . . Tma C . . . . . n . . . . . .

Table p Regression estimates for short term models in equations (and (for Virginia. Regression R 's are - p and - 7 respectively. Model (has a D statistic of - -

	Equation (		Equation (	
Variable	Coe- cient	t value	Coe- cient	t value
Constant	- 77	-	- 7	-S
HD	-	- p	-	- S
CD	-	- S7	- 7	-
HD	-	-S	-	-
CD	-	- p	-	-
Day Hour	-	7 -	-	-S
Day Hour	- 7	-	- 7 7	-
Day Hour	- S	-	- 7	- 7
Day Hour	-	S -	-	- S
eek Hour	- p S	- 7	- 7p	- S
eek Hour	- S	-	-	-
eek Hour	- p	-	- 7	-
eek Hour	- 7	-	- S	-
Month	-	- 7S	-	-
Month	-	- 7	-	-
Month	- S	- p	- S	- p
Month	-	- 7	-	-
Y	-	-	-	- 7
Y	- p7	- 7	-	-
Y	-	- p	-	-
HOL	-	- 7	- 7	-
SAT	- p	p S	- 7	-
SUN	-	- p	- p	- 7
$t-$			- p	- 7
$t-$			p p	-
$t-$			- p	-S
$t-$			-	-
$t-$			p	S S
$t-$			-	7

Table · MAPE of models (