



# Statistical Analyses and Applications in Regulating Electric Utilities: Michigan Practices

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- I. Generation and Certificate of Need Section
  - (i) Load Forecasting
  - (ii) Natural Gas Market Modeling
  
- II. Energy Data and Security Section
  - (i) Michigan Energy Appraisal (MEA)
    - short run energy market forecasting

# Load Forecasting Models

- Most annual load forecasts, whether peak demand or energy, are outputs of either the linear or logarithmic family of functions

Linear  $\rightarrow y = \beta * x + \alpha$

Log  $\rightarrow y = \beta * \log(x) + \alpha$

- $\beta$  and  $\alpha$  are fixed values which specify the relationship between  $x$  and  $y$ .
- Either the exact or estimated values of  $\beta$  and  $\alpha$  are determined through *regression analysis*.
- Whether  $\beta$  and  $\alpha$  are exact or estimated depends on whether the data represents the entire population or just a sample of the population. Calculation of  $\beta$  and  $\alpha$ , as well as, interpretation of what the regression says about the data is critically dependent on this distinction

- In reality, building a model that predicts something as complicated as energy consumption usually involves more than just one explanatory variable like GDP.
- Weather, customer type, income, price levels, A/C saturation, building codes, ect., all will have an effect on energy consumption
- Assuming we want to stick with a linear model, the generic regression would look something like:

$$y = \beta_1 * x + \beta_2 * m + \beta_3 * n \dots + \alpha$$

where y is energy use and x, m and n are explanatory variables such as GDP, temperature, price, ect.

# The General Form


- Utilities tend to break up the load forecast by customer class. There are forecasts for residential customers, commercial customers and industrial customers.
- In some cases, the customer groups may be broken down into more specific groups. An example, would be dividing the commercial class into subgroups based on the type of service offered.
- Load forecasts are developed for each subgroup and then the total expected energy use of demand for each year is added together to get a total load for the utility.
- For each subgroup, the industry standard is to develop two regressions. The first models and forecasts use per customer and the second models and forecasts the number of customers.

# Combining End-Use and Econometric Approaches

## Forecasting Residential Sales

### Model:

$$\text{Residential} = \text{Number of Customers} * \text{Appliance Penetration} * \text{Use per Appliance}$$



Forecasted from housing permit data and historical data and by relationship between housing permit data and new customers. Also includes foreclosures.

Forecasted from Residential Saturation Survey data performed biennially.

Projected from trend, incorporating energy efficiency .

### Notes:

- The method is applied to 38 different appliances.
- “Forward - looking” appliances capture new and existing small appliance growth.
- Some customers own multiple units of room air conditioners, TV’s, etc., and these are included.
- Government mandated appliance efficiency standards are in place.

# Industrial Models

- Both CMS and DTE break their Industrial customers into automotive and non-automotive customers.
- Separate regressions are built for each
- In some cases, regressions are not used to predict energy usage. Rather, usage for a particular customer may be projected based on a specific business plan or outlook

# The Autos

- CMS defines GM/Delphi as one customer class in and of itself
- The regression predicts use per fiscal quarter (Q) and then adds up the quarters for the year:

$$Q_N = \beta_5 * I + W$$

Where  $I$  is the Michigan Transportation Equipment Employment indicator and  $W$  is a fixed-number seasonal adjustment for particular months.

- $I$  is built from Global Insight's 30 – yr Michigan Transportation Equipment Employment projection



- DTE breaks down its automotive sales class into six subgroups:
  - assembly plants, stamping plants, power/drive train plants, other parts plants, administrative facilities, other transportation
- A regression is built for each sub group and then added together to get the total expected sales for the class
- DTE's presentation did not reveal their actual regressions. However, the following explanatory variables were identified:
  - local auto production, U.S. auto production, plant additions/closures, efficiency improvements and 2<sup>nd</sup>/3<sup>rd</sup> shift operations

# The Non-Autos

- CMS uses the following basic model to get annual figures for this class (NA):

$$NA = \text{Ave. Hourly Use} * 24 * \# \text{ of billing cycle days}$$

- A regression for Ave. Hourly Use ( $H$ ) is built based on quarterly baseload trends and Michigan industrial production index:

$$H_n = \beta_6 * b + \beta_7 * s + \beta_8 * m$$

Where  $H$  is the quarterly usage,  $b$  is the quarterly baseload,  $s$  is the Michigan Six Sector Production Index and  $m$  represents a specific month (1-12).

- DTE breaks down its non- automotive sales class into 10 subgroups:
  - metal fabrication, mining, chemicals, manufacturing equipment, petroleum, non-metal processing, steel, rubbers/plastics, other manufacturing, equipment
- A regression is built for each sub group and then added together to get the total expected sales for the class
- DTE's presentation did not reveal their actual regressions. However, the following explanatory variables were identified:
  - fabricated metal production, steel production, closed plants, rubber/plastic production, local auto production, Big 3 use of plastics

# Forecasting Peak Demand

## CMS's Methodology

- Uses historical system peaks from 1976 to 2008 to build a regression that estimates temperature sensitive load
- Coincident base hourly usage for each customer class is estimated and then subtracted from actual peak load to get an estimated quantity of temperature sensitive load – method of estimation for base hourly load is not presented
- To explain the yearly change in temp sensitive load, CMS looks at temperature levels at time of peak, AC saturation levels, number of customers with central air and humidity levels
- While CMS's historical analysis attempts to quantify the influence of humidity and extreme temperature, its forecast beginning in 2009 assumes no extreme temperature/humidity conditions in the future

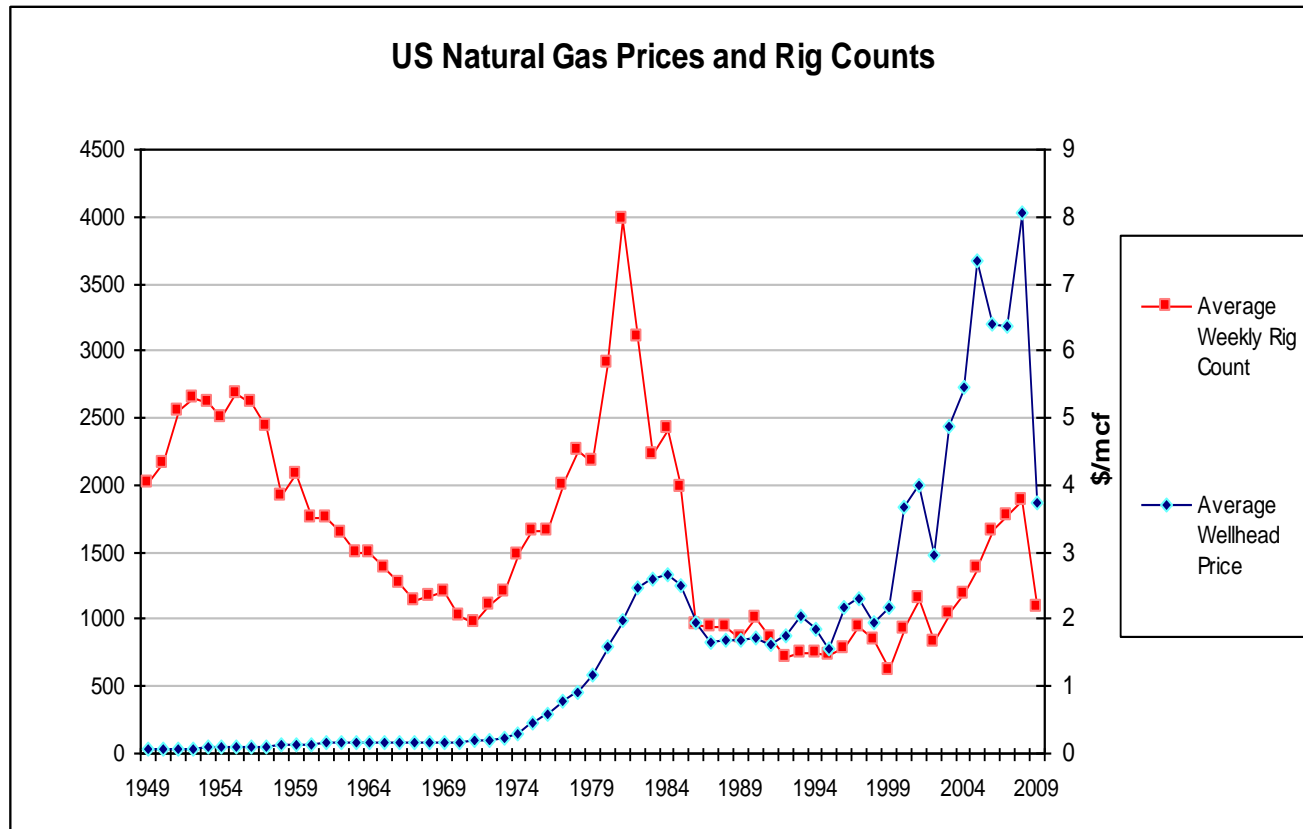
- Forecasted temp sensitive load at time of peak is the following

$$L_t = \beta_1 * (\text{Residential Customers} * \text{AC saturation} * \text{AC efficiency index} * [\text{peakday maxtemp} + \text{peak day average temp}] / 2) + 968.095$$

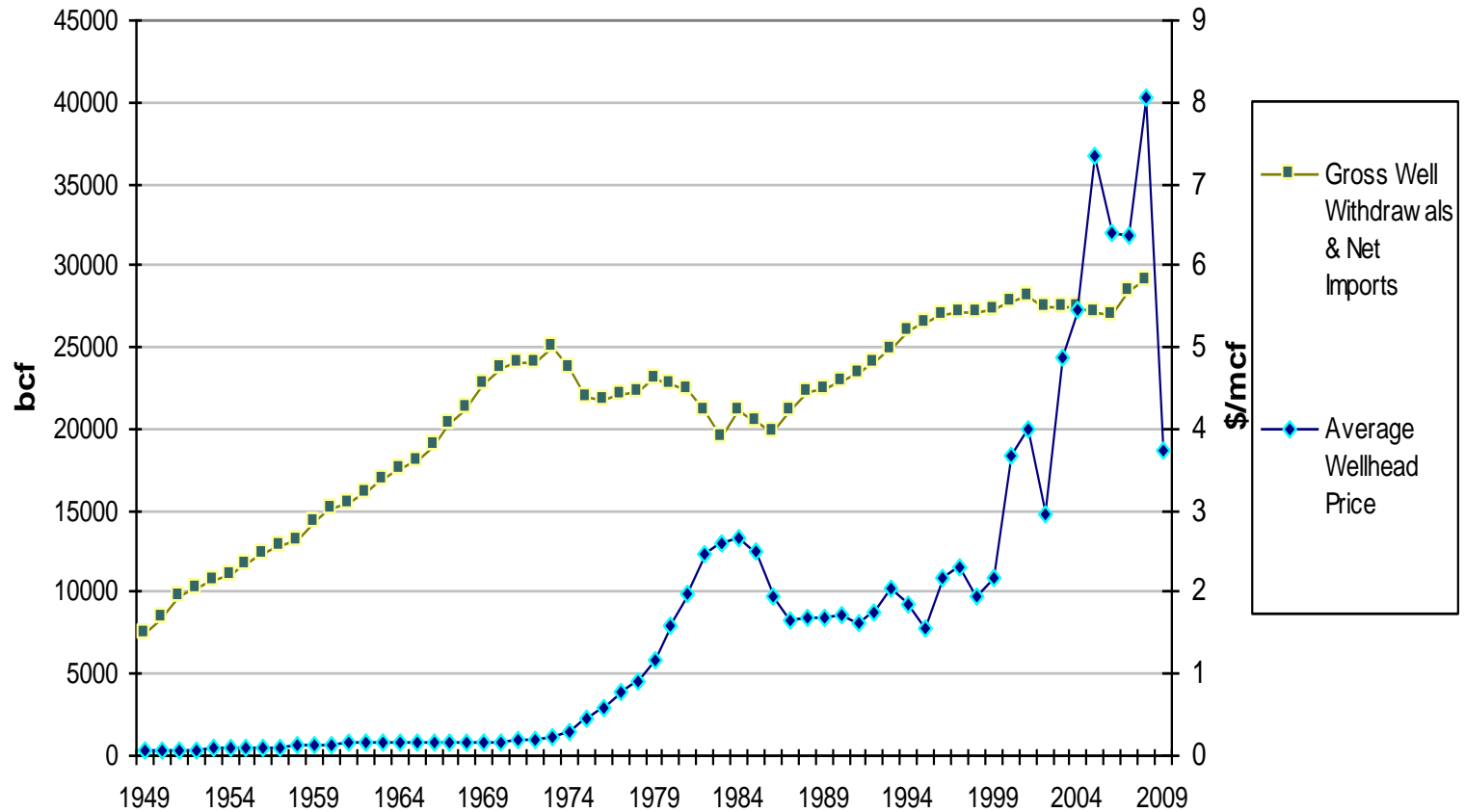
- Residential customers, AC saturation & efficiency and peak day temps are all themselves forecasts
- Forecasted temperature sensitive load is then added to separately forecasted coincident base hourly usage for each customer class to get a total system peak

- EE is built into presented peak forecast by taking annual energy efficiency impacts estimated in each year and dividing that number by the number of hours in each year – this converts energy to demand
- Hourly average is then multiplied by 1.255 to estimate the EE impact during peak
- Direct load control is built into forecast beginning in 2011
- Demand response is built into forecast beginning in 2012

# Natural Gas Market Modeling & Forecasting

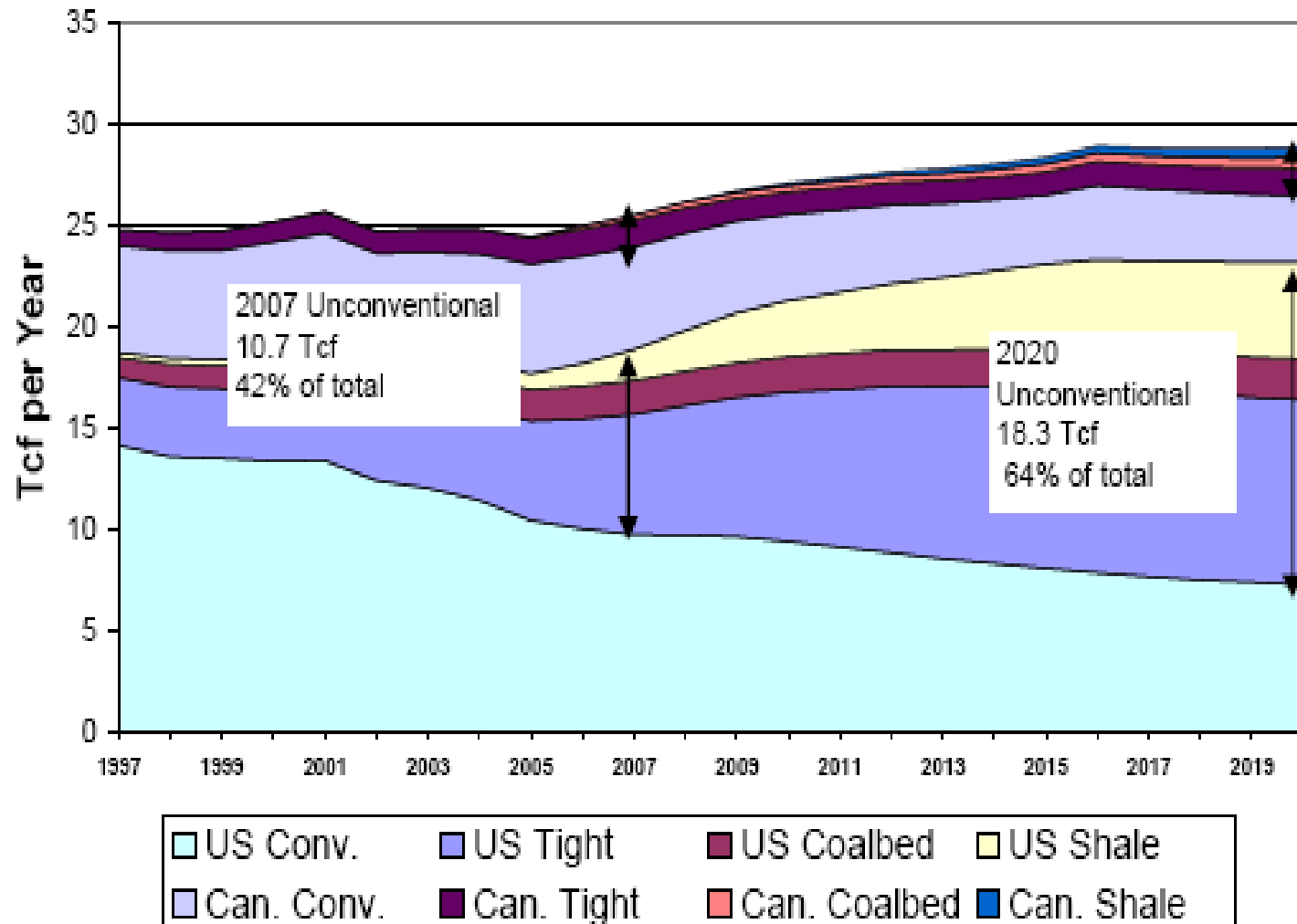


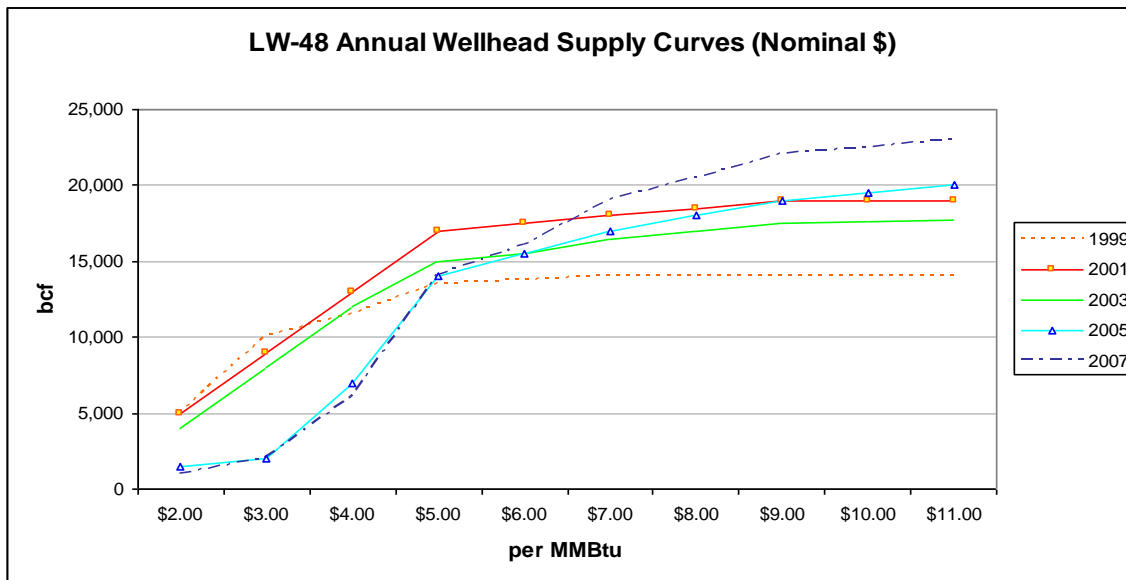
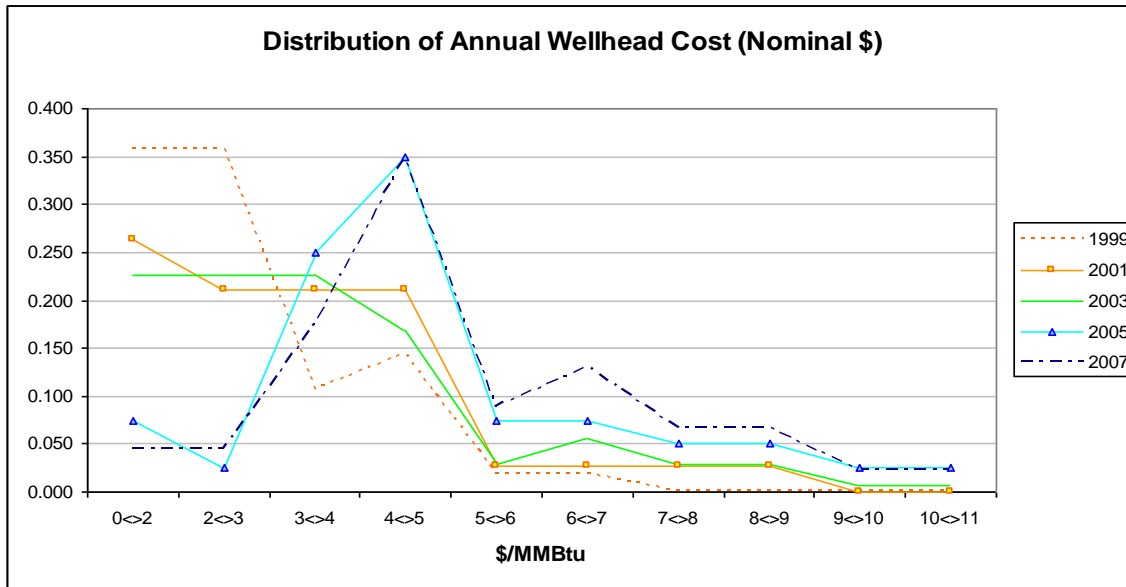
## US Natural Gas Prices and Production



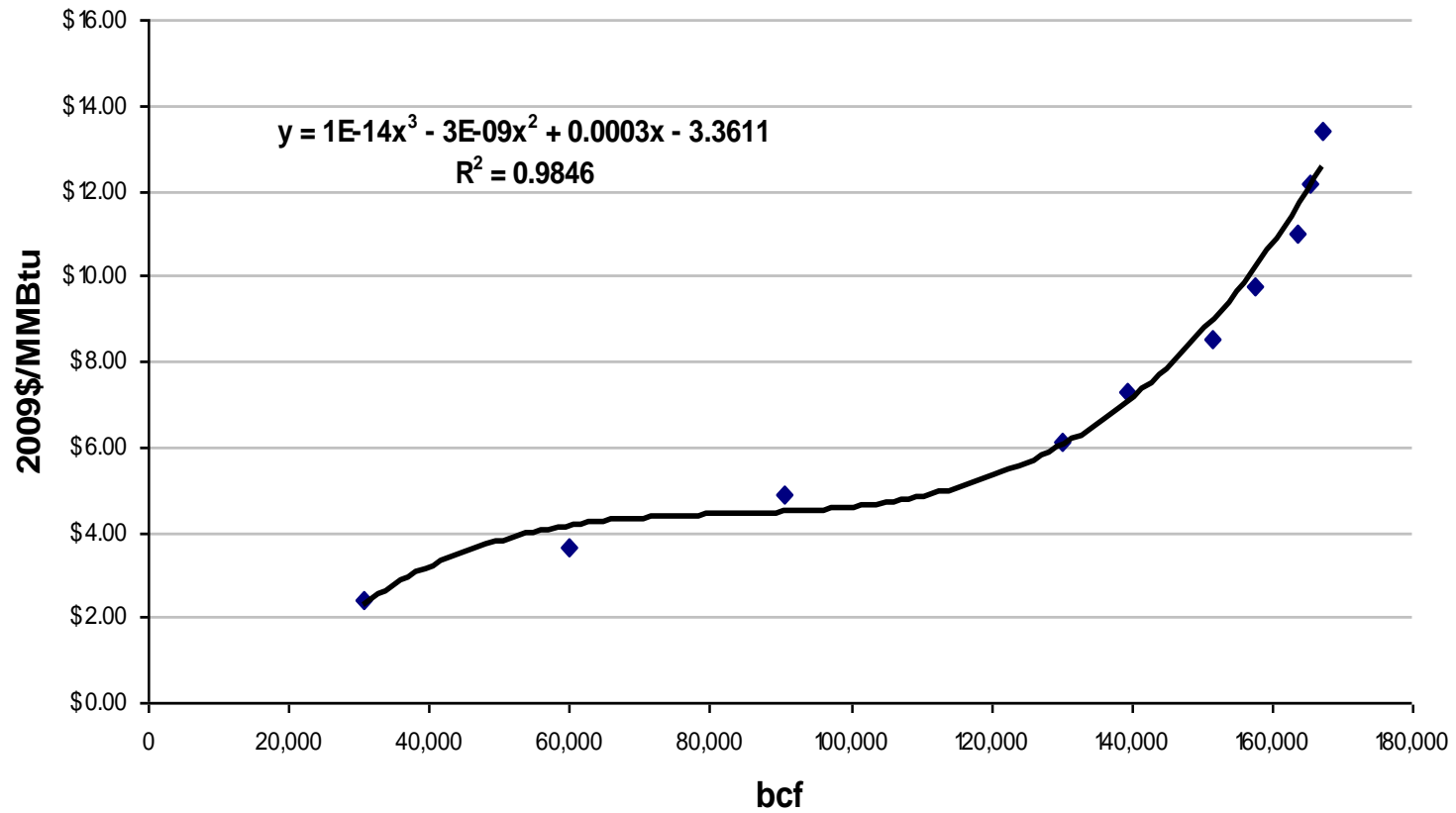


# Trends in Production

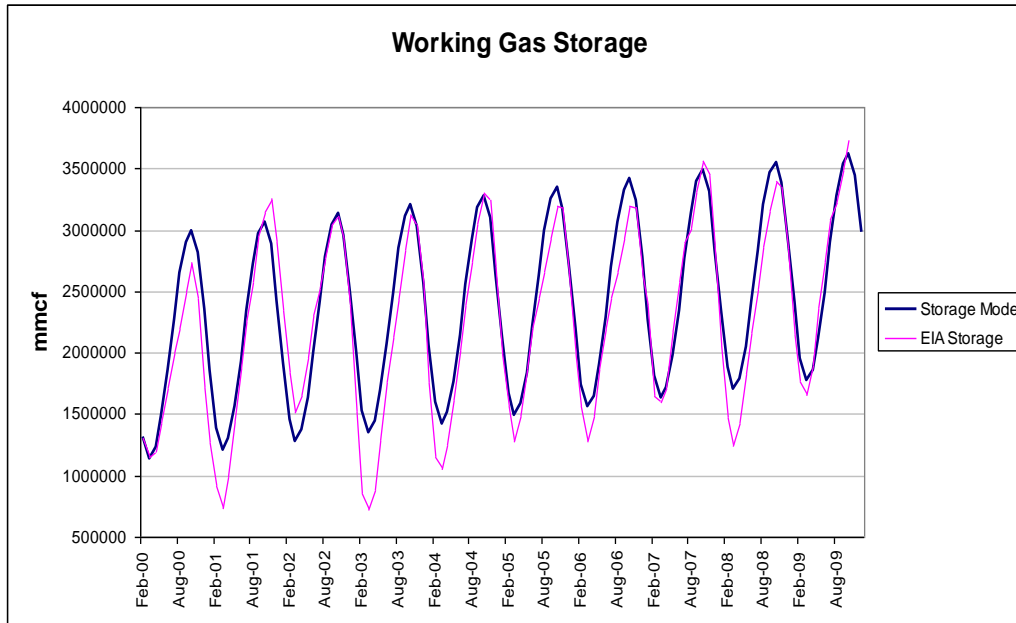




## LW-48 Wellhead Natural Gas Supply Curve 1999-2007



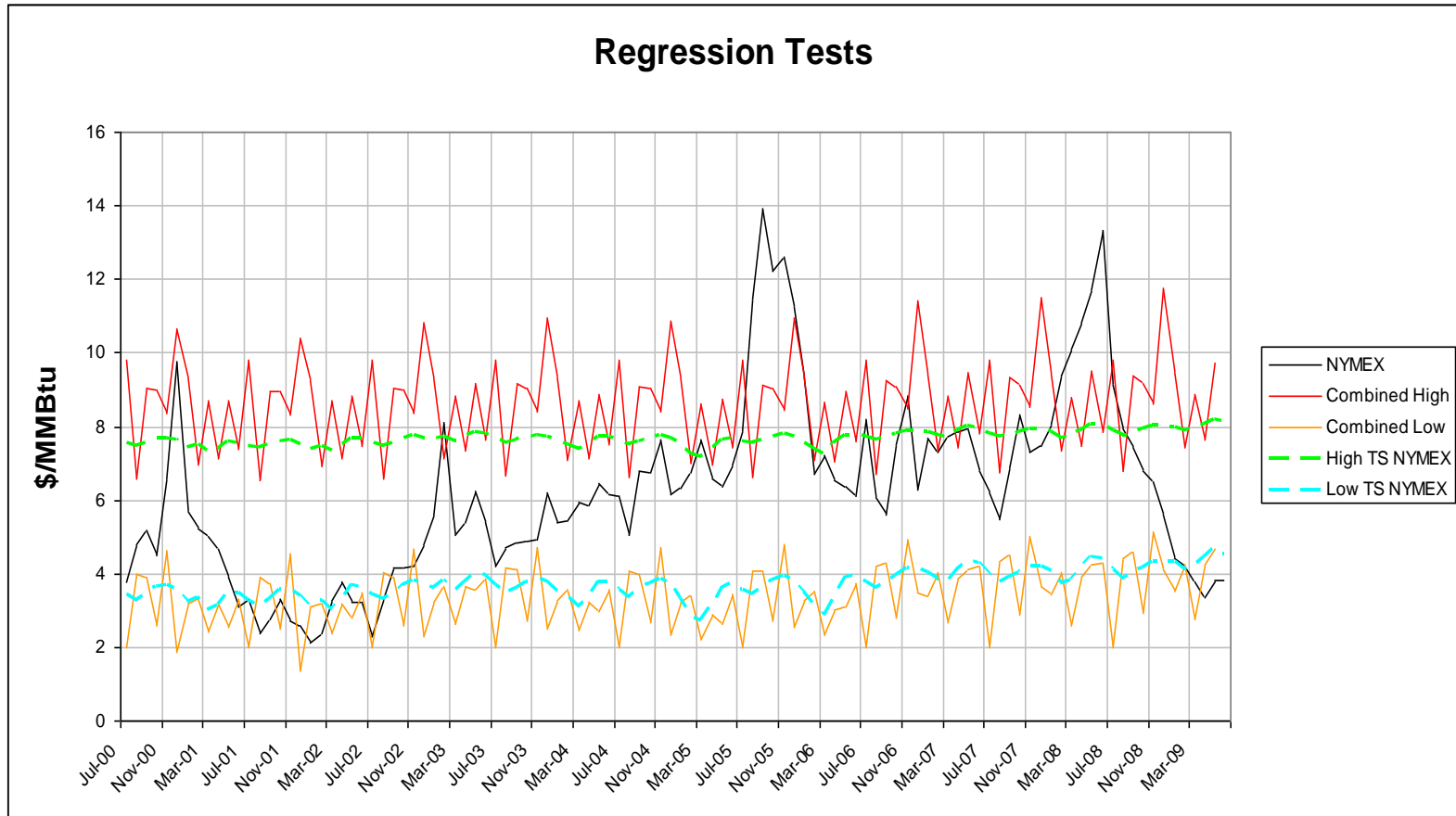
# Modeling Storage Trends



**Storage = 927182\*sin( $\Theta$ \*3.14/12)+Moving  
Midpoint Function**

Month		$\Theta$
January	→	13.200
February	→	15.600
March	→	18.000
April	→	19.714
May	→	21.429
June	→	23.143
July	→	0.857
August	→	2.571
September	→	4.286
October	→	6.000
November	→	8.400
December	→	10.800

# Short-Run Pricing Models



**Assumptions:**

$$\text{NYMEX} = 0.091(\text{IPI}) - 3.571(\text{Stor})$$

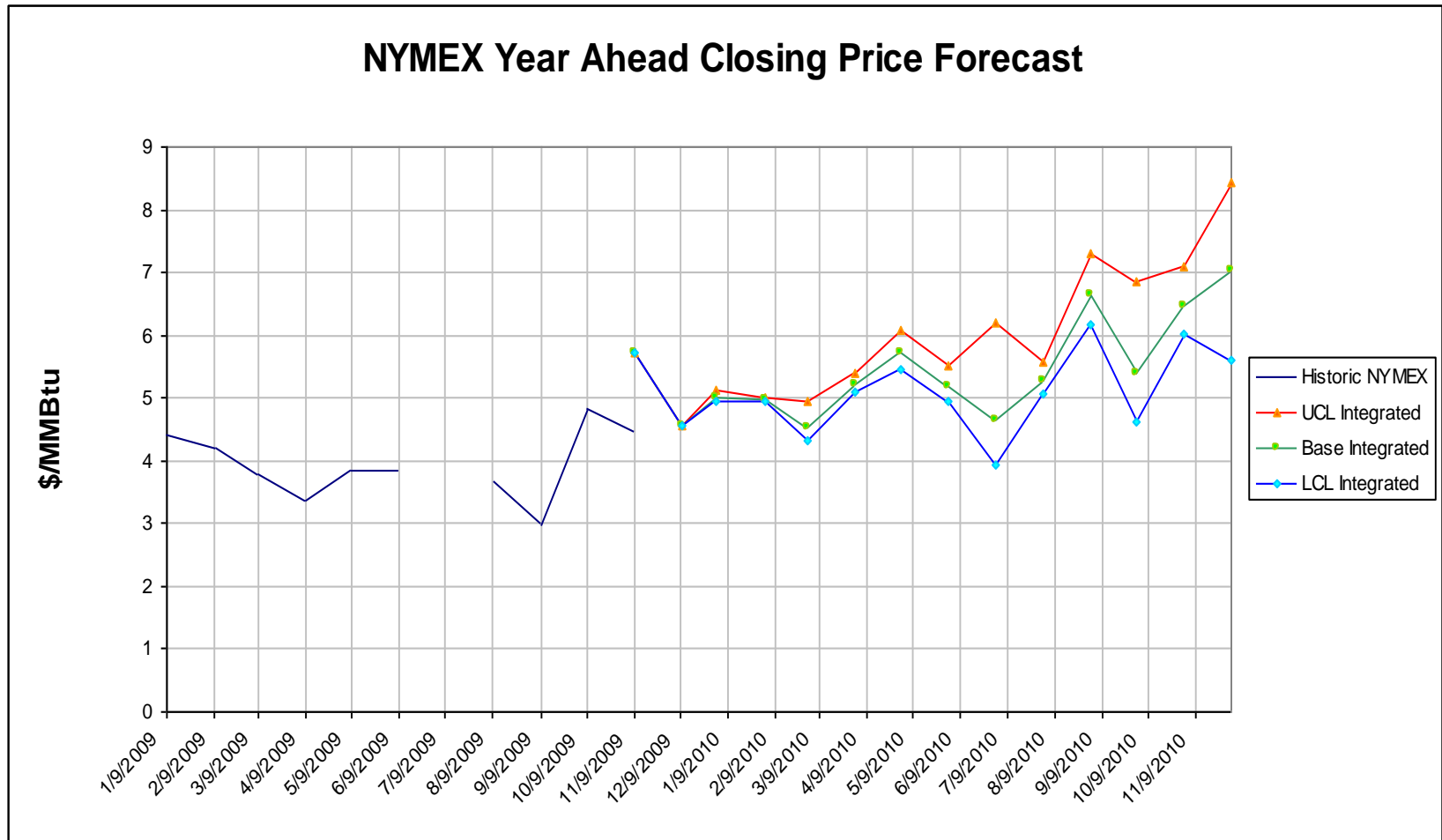
$$2010 \text{ Nominal } \% \Delta = [2\%, 4.8\%, 5.4\%]$$

$$\text{IPI } \% \Delta = 0.429*(2\text{-qrt ave current gdp } \% \Delta) - 0.020$$

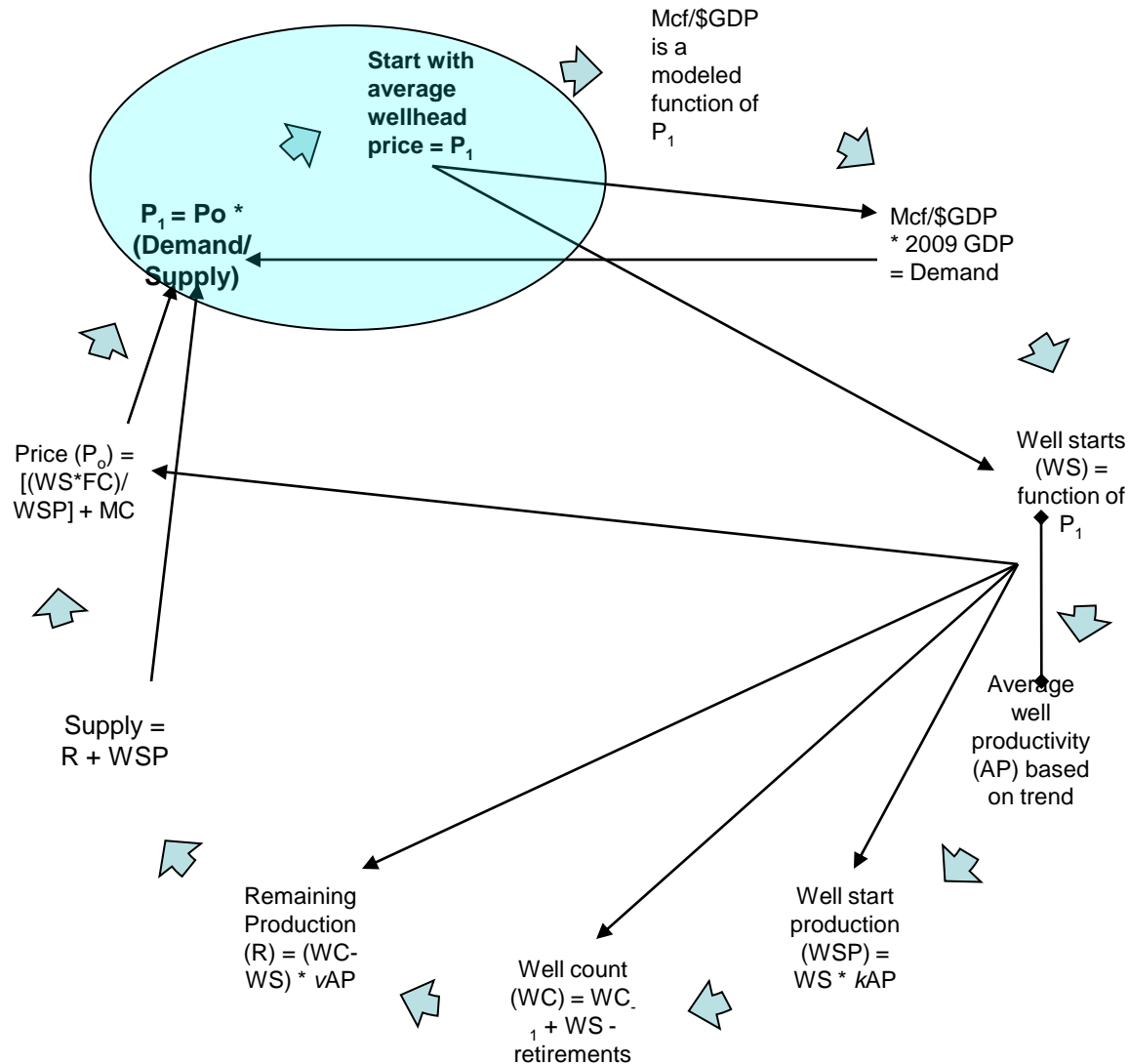
$$\text{Storage} = 927182*\sin(\Theta*3.14/12) + \text{Moving Midpoint Function}$$

Month	$\Theta$	Regressions
January	13.200	$.278*\text{IPI} + .440*P_{-1} - 25.210$
February	15.600	$.870*P_{-1} + .488$
March	18.000	$.448*P_{-1} + .283*\text{IPI} - 26.351$
April	19.714	$.910*P_{-1} + .436$
May	21.429	$1.006*P_{-1} - 2.478*\text{Stor} + 3.053$
June	23.143	$.997*P_{-1} - .171$
July	0.857	$.502*\text{IPI} - 46.415$
August	2.571	$.625*P_{-1} + 1.867$
September	4.286	$1.231*P_{-1} - 0.153$
October	6.000	$.639*P_{-1} + 0.241*\text{IPI} - 22.832$
November	8.400	$.931*P_{-1} + 1.228$
December	10.800	$.712*P_{-1} - 8.065*\text{Stor} + 10.976$

# Short-Run Forecasts

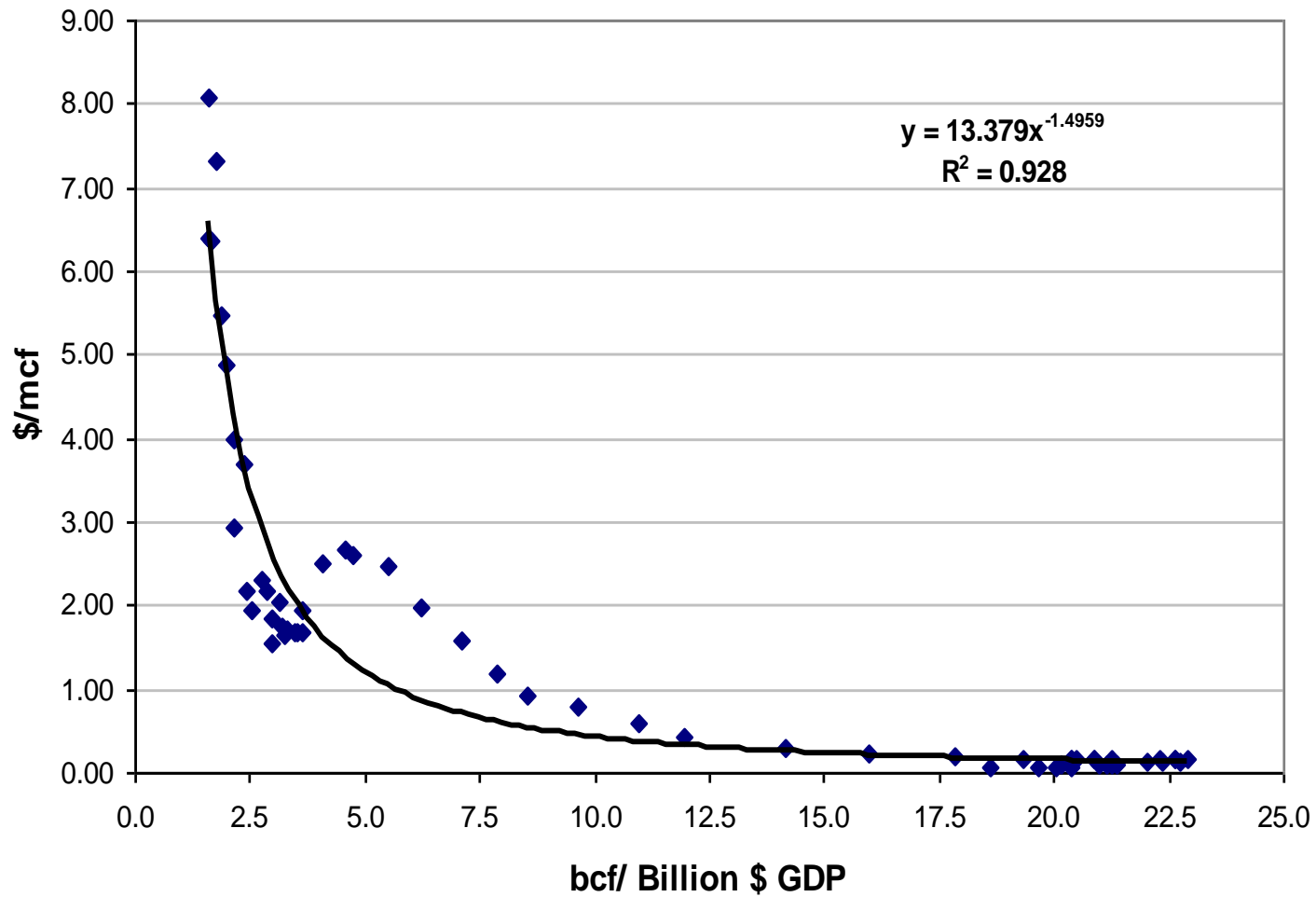


# A Long-Run Equilibrium Approach

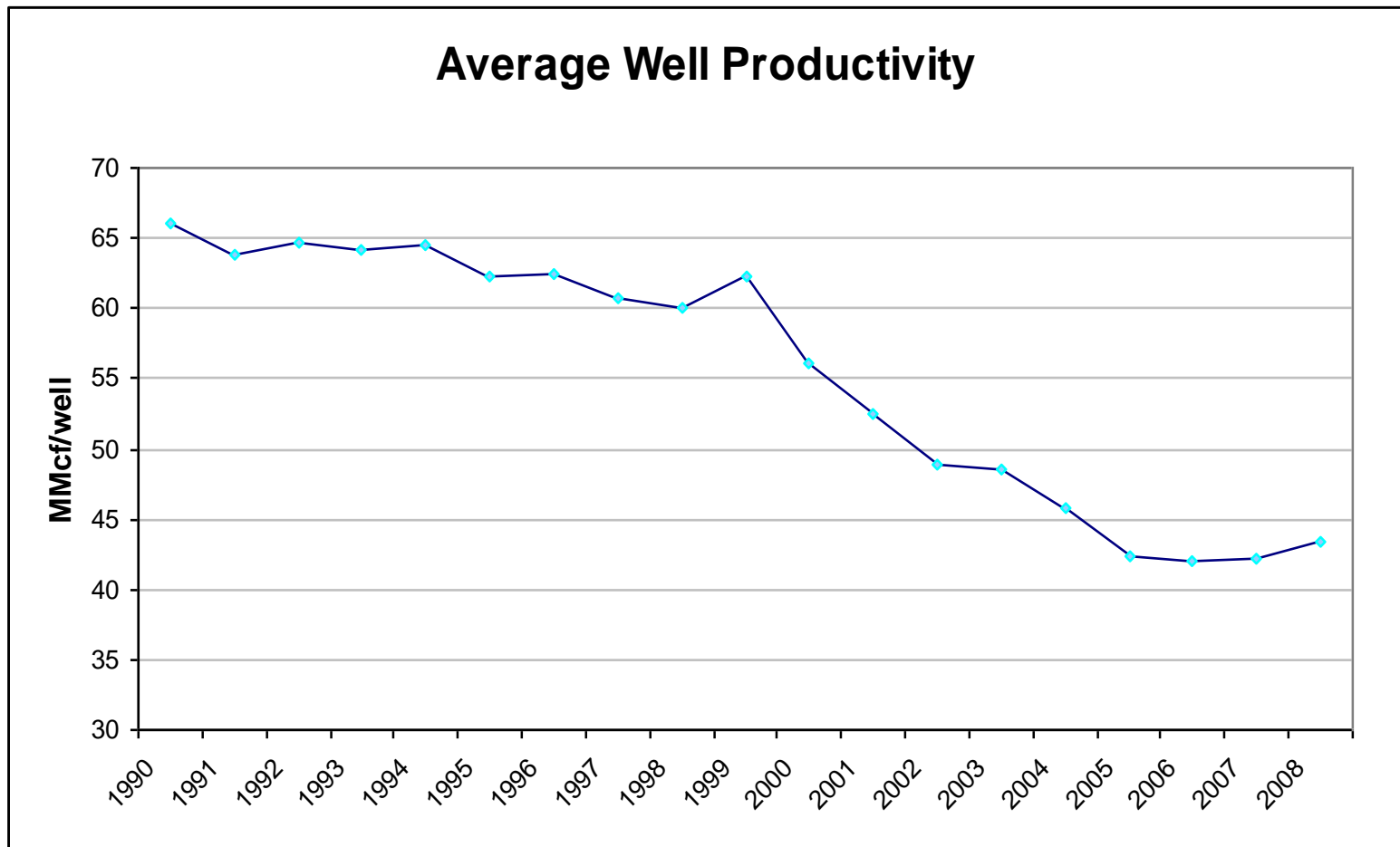




## Historic Demand Trend (Nominal Dollars)



# U.S. Average Well Productivity Trend



# Producer Profit Maximization

*If*

Well count =  $WC$

Well productivity/unit of time =  $WP$

Wellhead price =  $P_{EIA}$

Production costs =  $L\&O$

Exploration, drilling and completion costs = exploration cost + (drill + complete  
time/ well \* drill + complete day rate)  
=  $FC$

*Then*

$$\partial \Pi / \partial WC = (WP * P_{EIA}) - [(WP * L\&O) + FC]$$

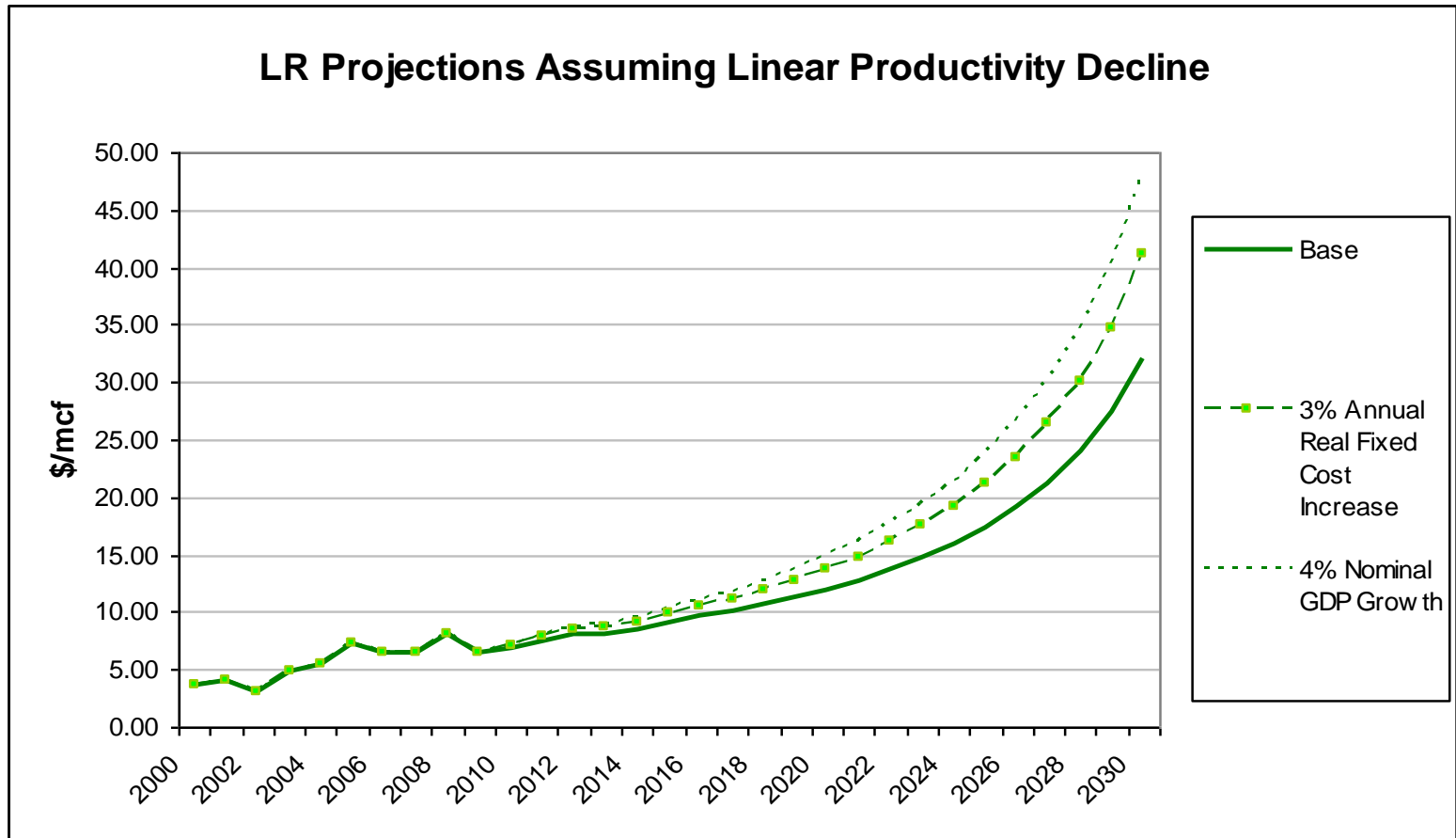
$$0 = WP * P_{EIA} - [(WP * L\&O) + FC] \rightarrow$$

$$WP * P_{EIA} = (WP * L\&O) + (FC) \rightarrow$$

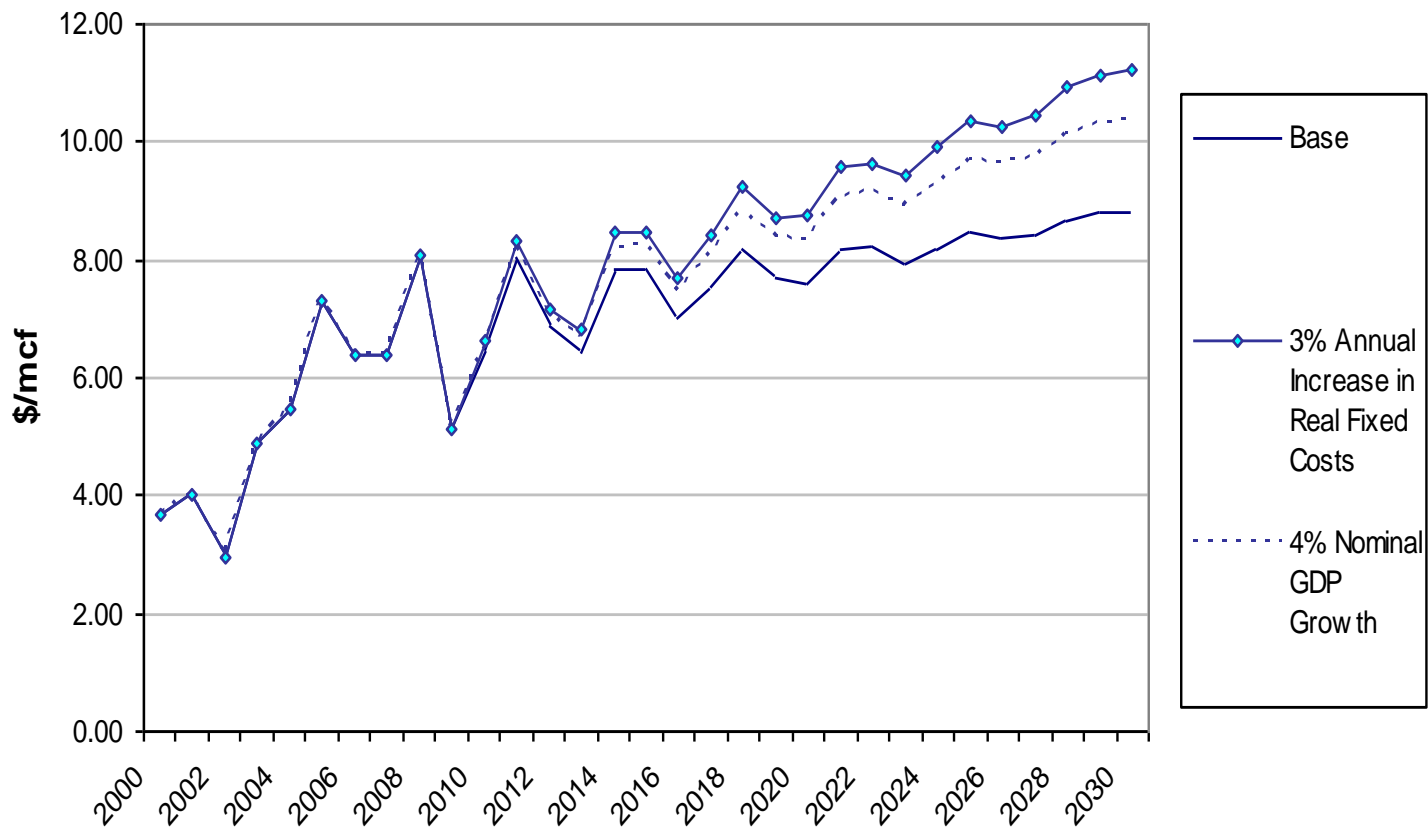
$$P_{EIA} = (WP * L\&O) / WP + (FC) / WP \rightarrow$$

$$\mathbf{P_{EIA} - L\&O = (FC) / (WP)}$$

# Long Projections Under Multiple Scenarios



## LR Projections Assuming Polynomial Productivity Decline Rates



# Questions & Answers