Chapter 1

Evolution of Forecasting Techniques for Dynamic Energy Markets

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We are in a very dynamic period in our domestic and global energy markets. Market forces are at work in both the shale oil and gas revolution and the development of renewable energy, which are dramatically impacting the energy industry. Transformation of global energy markets highlights the importance of understanding various forecasting methods and technical methods to accurately forecast in such a dynamic market structure. This chapter provides a comprehensive review of the forecasting techniques for energy markets and illustrates them through a case study. This chapter can potentially be utilized by academics and industry practitioners for understanding the evolution of the energy market dynamics.

Keywords: Energy forecasting; energy markets; time series analysis; applied econometrics methods.

1. Introduction

Forecasting in the energy sector is similar to other industries that require forward-looking estimates of supply, demand, price in order to plan and operate the businesses. Forecast energy supply, demand and price has long been recognized as an important component of long-range energy planning and investment decision-making by energy companies.

However, the energy industry is more complicated than other industries in many respects, including the highly capital-intensive nature of the industry, the regulatory and policy oversight aspects that exist because of the importance of energy in our daily lives as a basic good and the unique economic attributes inherent in the

energy industry. The energy industry includes energy products that are used in daily activities, such as gasoline for transportation (which uses crude oil as a feedstock), natural gas for home heating and as an input fuel to generate electricity in the power sector and electricity for heating, lighting and air conditioning.

In addition, the operation of energy sector is highly technical. The oil and gas business requires sophisticated upstream operations, including development of underground or deep ocean crude oil and natural gas fields, drilling and operating the wells that recover crude oil and natural gas to the surface that then utilizes a sophisticated pipeline network (and other transportation options, such as vessels, barges, rail and trucks for crude oil) to deliver products to downstream refineries, power plants, other industrial, commercial and residential customers utilizing distribution networks to deliver energy products to the end users. Electricity is the most complex energy product due to the non-storable nature and other engineering complications with the transmission of power that relies on instantaneous generation of power that must exactly match the moment-to-moment changes in demand from the changes in our daily activities. Further technical operating complications have grown with the integration of renewable energy resources into the electricity sector, which are non-controllable and generate electricity when the renewable energy is accommodated (i.e. when the sun shines and when the wind blows). Further, distributed energy such as residential solar Photovoltaics (PV) enables consumers to produce some of their own electricity demands and sell excess power back to the electricity market, which shifts power flows from traditional paths [SEIA, 2017].

Due to the importance of the energy industry to the economy as well as the high capital cost and technical nature of the energy industry, historically there has been substantial governmental focus on energy forecasting. Many developed nations have governmental agencies responsible for developing long-range forecasts of energy demand and supply that may aid in the development of government policies to ensure adequate capital investments to provide reliable supply of energy in order to meet the country's needs with the lowest possible cost (i.e. energy security). Governments of industrialized nations typically use these forecasts and other agencies focused on the implementation of regulation of the energy sector (rate, environmental, etc.).

In addition, energy market participants develop their own forecasts which can be shared (e.g. BP and Exxon) or used solely for their own business decision-making. Academics, think tanks, consultants and other independent entities may conduct energy forecasts for industry use and decision-making.

Forecasting has become even more critical for various energy markets in the recent years. The development of competitive wholesale electricity markets, in the

US and elsewhere rely on demand forecasting as a key component for dispatching the available generators at the minimum cost. Furthermore, technological innovations and other developments across the energy sector not only create additional challenges in forecasting energy markets but also increase the importance of forecasting to aid in energy planning and business decision-making [Hong, 2014; Armstrong and Brodie, 1999].

We will highlight the econometric methods used in forecasting energy markets. Econometrics methods are appealing because these methods are built upon the economic theory [Bhattacharyya and Timilsina, 2009]. Econometric methods have been widely used by academic researchers and industry practitioners. This chapter will provide an in-depth review of the challenges of dynamics for various energy markets and econometric models on forecasting market dynamics using a case study.

Majority of the forecasting studies in the literature often focus on the forecasting approaches developed for a single energy source (e.g. natural gas forecast). This chapter differentiates from the existing literature by providing a comprehensive review of the market trends for multiple energy sources and highlights the importance of forecasting methods from different energy market perspectives. We cover the market dynamics of multiple energy sources and address the challenges for forecasting these markets. Further, this chapter contributes to an understanding of the complex nature of the energy markets by presenting an overview of various energy market dynamics and the use of forecasting in these dynamic market environments. We also introduce the fundamentals of the underlying economic theory of general equilibrium in this chapter in addition to a practical industry example.

Finally, we studied a practical industry example of forecasting prices for Renewable Electricity Credits (RECs) using the time series method. This is a widely used forecasting method in both academic and industry studies. This practical example provides a forecast for the movement of the future REC prices along with the changing commodity prices under the changes in federal policies. The approach we employed also considers the causal relationship between the dependent and independent variables. Overall, we found that the regional electricity prices in NEPOOL affect future REC prices but not regional electricity prices in PJM. We also found that there is no significant impact of REC prices on the wholesale electricity prices.

The purpose of this example is to introduce how one can analyze and understand the characteristics of time series data for forecasting as well as to introduce an approach to model construct, model testing and estimation outcomes. Thus, this example should guide the readers on the basic steps for forecasting using a specific

time series model. It is important to note that we provided this as an illustrative example for the application of time series models and the analysis could substantially be expanded with additional model specifications and robustness testing.

The remainder of the chapter covers the evolution and challenges in forecasting energy markets in Section 2. Applied Methods for forecasting energy markets are discussed in Section 3. Finally, Section 4 provides a case study from renewable energy markets to illustrate a practical application of the forecasting methods.

2. Evolution and Challenges of Forecasting Energy Markets

Substantial developments in the energy industry have occurred across the energy sector, including technology innovations, policy/regulatory reforms, resource shifts and other market dynamics.

Heightened recent focus on energy market forecasting methods have resulted due to the recent substantial development in the energy industry. These development take the form of both market and non-market changes, which have created tremendous variability in market dynamics across the energy sector. Market dynamics affect supply and demand as well as market prices. More accentuated market dynamics, in terms of the order of magnitude of unpredictability or the increased number of factors affecting supply, demand and prices, create an ever-challenging environment to forecast energy markets. Therefore, forecasting energy markets has become more challenging.

Further, due to the interrelated nature of the energy sector, changes in one energy sector can affect other energy sectors. In another example, since natural gas is an input fuel to generate electricity, any change to the economics of natural gas will impact the economics within the electricity markets. Consequently, these collective substantial changes have and can be expected to lead to changes in energy market dynamics, characterized by significantly greater uncertainty in supply, demand and pricing.

By way of background, energy forecasting has evolved tremendously in the past 40 years since the 1970s oil crisis brought focused attention to the impact of energy on consumers and the economy. [Bhattacharyya and Timilsina, 2009]. In the 1980s, simplified methods of energy demand forecasting had been documented in numerous countries, including reliance on energy intensities or an elasticity of energy demand with respect to national income or GDP [Westoby and Pearce, 1984; Codoni *et al.*, 1985]. For example, simple measures of GDP elasticity and energy intensities have been used to forecast energy demand and develop energy policies in China and India [GOI, 2006; Berrah *et al.*, 2007].

The forecasting techniques developed generally comprise three categories of approaches as follows [Bhattacharyya and Timilsina, 2009]:

- econometric models grounded in the economic theories that seek to validate the economic rules empirically;
- engineering-economy models (or end-use models) that attempt to establish accounting coherence using detailed engineering representation of the energy system;
- combination or hybrid models that combine the features of the two traditions of econometric and engineering models.

As discussed above, the focus of this chapter is on econometric methods used to forecast energy. An econometric model is a quantitative approach to establish a statistical causal relationship between the dependent (i.e. outcome) variable and the selected independent variables by using historical data. The statistical relationship can be used to forecast changes in the independent variables and determine their effects on the dependent variable [Varian, 1992].

Econometric estimations are frequently used to forecast energy demand. Major developments in econometric estimation methods have occurred particularly since 1990. According to Griffin [1993], there are three major developments in energy forecasting, including the trans-log revolution, the panel data methods and the discrete choice method [Wirl and Szirucsek, 1990]. These methods are evolved from the basic ordinary least squares approach and allowed researchers to analyze complex energy data empirically. This allowed investigations into capital energy substitutability and technical change questions. A large number of studies applied the trans-log model at the aggregated and disaggregated levels, including Christopoulos [2000], Dahl and Erdogan [2000] and Buranakunaporn and Oczkowski [2007]. Even the econometric analysis has been applied to the entire energy system using the energy balance framework (e.g. see [Adams and Shachmurove, 2008]). Below, we provide a short overview of primary energy sources and related challenges for predicting the future for these energy sources.

2.1. Crude oil

Crude oil is currently the single most dominant energy product consumed for the entire global energy industry. On a global basis, crude oil has a more than 30% share of the primary energy [BP Energy Outlook, 2016]. Within the US, crude oil products accounted for 36.6% of the primary energy consumption in 2015 [EIA, 2017]. An important economic characteristic of the crude oil industry is that it is a global market with significant trade occurring among countries.

Forecasting global crude oil markets has always been challenging due to the difficulties in understanding the supply and demand outlook for all of the distinct economies across the globe along with the difficulties in forecasting the decision-making of the OPEC cartel in its goals to control prices through production limits.

However, with the game-changing oil production technological developments that occurred over the last decade in the US, forecasting crude oil markets has become much more challenging. The oil and gas industry has enabled cost-effective extraction of oil and gas resources from shale rock using hydraulic fracturing and horizontal drilling which led to substantial production increases in the US. Shale rock holds substantial oil and gas resources but without the technological breakthrough, it could not be economically extracted. This abrupt shift led to the US substantially reducing imports of crude oil to meet US refinery demand and to begin to export crude oil production that extends beyond domestic needs. This technology breakthrough has materially impacted the global crude oil markets in terms of market supply and pricing, therefore, introducing challenges for forecasting global crude oil prices. Figure 1 presents the historical global crude oil prices.

Fig. 1. Historical Brent and West Texas Intermediate (“WTI”) spot crude oil prices (\$/bbl).

Notes: Global crude oil prices showed a precipitous decline in mid-2014 with prices falling from a peak of \$115 per barrel in June 2014 to under \$35 per barrel in February 2016. Prices have begun to stabilize in more recent months with the figures largely fluctuating around \$50 per barrel since late 2016 [EIA, 2018].

There are numerous economic factors that have contributed to the free fall in crude oil prices. First, on the supply side of the equation, the large increase in production from the US shale producers added substantial quantities of supply to the global crude oil market beyond historical levels. In the US, the primary shale crude oil production basins include the Bakken basin located in North Dakota, numerous basins located in Texas including Eagle Ford and the Permian Basin as well as Niobrara (Colorado and Wyoming). Since 2008, US unconventional shale oil production increased substantially from approximately 0.5 million barrels per day (BPD) in 2008 to over 4.5 million barrels per day in 2014 [EIA, 2017]. All else equal, an increase in supply will reduce the market-clearing price.

Importantly, OPEC decided not to make a cut in production levels as it had historically done which would have caused prices to rise by offsetting the increased US production. OPEC's reversal of its past cartel behavior could have been driven by its desire not to help the US shale producers with higher prices (while it lost sales volumes). In addition, OPEC had an economic incentive to maintain its market share in the growing Asian economies.

On the demand side of the equation, lower-than-expected demand resulting from slowing growth in emerging markets, most importantly in China, caused demand growth to lag behind historical levels. The stunted demand was exasperated by the strong US dollar. Crude oil is traded in US dollars and a strong dollar translates to reduced purchasing power of countries that are consuming crude oil. No major energy forecasting organization that we are aware of predicted the precipitous fall in crude oil prices that occurred in the middle of 2014. Figure 2 shows crude oil spot prices and crude oil forward price curves during the period January 2014 to December 2014.

Within the global crude oil market, the prices of crude oil futures contracts traded on exchanges such as the New York Mercantile Exchange or the Intercontinental Exchange are commonly perceived to reflect the expectations of market participants about the future course of crude oil prices [Alquist and Arbatli, 2010]. The futures market provides an important role in information aggregation and price discovery available. The price discovery process involves the interactions of buyers and sellers in the market prices to determine the market price of an asset. The futures market serves an important function of price discovery as informed individuals with judgement participate in these markets to take advantage of new and emerging industry information, which causes price movements to occur commensurate with timely actions taken by market participants in response to new and relevant information. Future markets react quickly to forward-looking information and the transaction cost is much lower in these markets than in the spot market, which

Fig. 2. Evolution of Brent crude oil price forecasts (\$US/barrel).

Notes: The forward price curves reflect actual market transactions by market participants that show their then current short-term forecast of crude oil prices. This figure highlights the free fall of crude oil prices, even when market participants continued to believe prices would bottom and rise somewhat and then remain flat [Financial Times, 2014].

further facilitates activities in the futures markets, leading to robust evidence of what is likely to happen and therefore relevant information for price discovery. However, as discussed above, market participants did not anticipate the substantial decline in crude oil prices during the precipitous fall in prices that occurred in the middle of 2014.

2.2. Natural gas

Natural gas has become an increasingly important fuel source in recent years as a result of technology developments, including the improving economics of shale gas, increasing production of natural gas and liquefied natural gas (LNG) processing, facilitating global trade of natural gas. In addition, the attractiveness of natural gas has increased because it is the lowest carbon-emitting fossil fuel and the US and other countries are becoming increasingly desirous of reducing carbon emissions.

Natural gas markets have historically been regional in nature because of the challenges of transporting natural gas over long distances. There are limited transportation options for natural gas transportation, including pipelines for land-based transportation of natural gas and expensive LNG transportation for waterborne

deliveries, which requires liquifying the gaseous product at the origin location and completing a regasification process at the destination location, along with specialized vessels to carry LNG.

Since there is currently no globally integrated market for natural gas, pricing mechanisms vary by regional markets. Understanding the natural gas pricing regimes and trends provides important economic characteristics to inform forecasting of natural gas markets. To put it into more regional context, we provide the analysis of US and Asian natural gas markets.

2.3. US regional natural gas markets

Natural gas price formation is driven by the regional natural gas markets, also referred to as pricing hubs in the US. Deregulation of upstream portion of the natural gas industry and the natural gas commodity process facilitated natural gas price formation in the regional markets.

Forecasting US regional natural gas markets has always been challenging due to limited storage capabilities, which exposes supply and demand to equilibrate more contemporaneously in each market. In addition, other factors that affect natural gas markets include weather conditions, proximity to demand, liquidity of supply at that point and current available capacity on pipelines within the system. Another factor that can impact prices is potential fuel competition, specifically with regard to electrical generation that occurs when the price of gas becomes more expensive than the next cost-efficient alternative, i.e. coal or solar power. This fuel competition can occur in the daily energy markets as well as for long-term energy supply/capacity decision.

Similar to crude oil markets, the US Energy Information Administration (EIA) did not forecast the price decline. US regional natural gas price forecasting became more complicated with the development of US shale gas. In early 2008, the potential of US shale gas to become a viable economic resource to be extracted and produced in substantial quantities was simply not on the radar as a feasible solution to the vast majority of energy industry professionals. The development of the US shale gas resources began in earnest around 2008 as a result of numerous factors.¹ The impact

¹Long-run energy forecasts projected insufficient quantities of natural gas for the US in close proximity and recorded-high natural gas prices during the time period, 2006–2008, creating strong economic incentives to find alternative sources of natural gas. As a result, some industry participants sought to determine if new (i.e. unconventional) methods of extracting natural gas could become economically viable with record-high natural gas prices and depressed outlook for future natural gas supply. With a focused effort, substantial technological innovations were rapidly observed in drilling horizontal wells in conjunction with a vertical well as well as injecting a specialized liquid substance

Fig. 3. Historical Henry Hub natural gas spot price (\$/MMBTU).

Notes: Henry Hub is a location in Erath, Louisiana, whose price is synonymously used with the NYMEX price of gas and is generally considered the benchmark price of natural gas in North America. In the US, natural gas spot prices have dropped 79% since 2008 from almost \$14 per MMBtu to about \$3 per MMBtu currently. The historical prices demonstrate numerous price spikes in the years 2001, 2005/2006 and 2008.

Source: Energy Information Administration (EIA).

of this development was substantial as the US has been able to substantially increase domestic production of natural gas rather than become heavily reliant on imported natural gas via LNG to meet domestic demand. Further, the US has enough natural gas supply to meet domestic needs and export excess to other countries. Since the shale revolution took hold in 2008, overall US natural gas production increased from about 55 Bcfd to 75 Bcfd by 2016, with the production estimated to double from 2015 to 2040.² The expanded natural gas supply resulting from the abundance of economically extractable natural gas resources has led to a general trend of reductions in natural gas prices. Figure 3 shows the US Henry Hub location.³

into the rock to fracture (or break) the shale sediment into small pieces, and loosen and capture the natural gas in a cost-effective manner. Substantial technological learnings occurred in years preceding 2008, with substantial breakthroughs in 2008 and further improvements since that time.

²The proportion of natural gas production made up by shale gas has increased from about 12% in 2008 to 53% by 2016, with a forecast of 65% by 2040. While shale gas plays are geographically distributed throughout much of the country, adding the Northeast, Rocky Mountains, Great Plains, the Southwest and even areas of the South to the traditional Gulf and Midcontinent production areas, the prime region of interest is the Appalachian Basin focused in the US Northeast. The oft-noted Marcellus play centered in Pennsylvania has been the main focus of the shale revolution to date, while the partially coextensive Utica play currently focused in eastern Ohio should comprise the next wave of shale gas growth. It should also be noted that there is much increased conventional natural gas production occurring in the Permian Basin in the Southwest, as evidenced by the strong 11% annual growth over the last 5 years to almost 6 Bcfd currently.

³Natural gas cost savings to consumers over this period could be more than \$175 billion, while associated electric cost savings could be more than \$200 billion. Further, the combination of low natural gas prices and abundant supply has helped foster increases in demand such as for industrial

2.4. Asian regional natural gas markets

Natural gas prices in Pacific Basin have historically been tied to crude oil prices. This phenomenon resulted because the historical contracting practices for natural gas products within Asian markets typically included those indexed to crude oil or petroleum product prices [EIA, 2015]. Internationally traded natural gas has been largely indexed to crude oil prices such as North Sea Brent or Japan customs-cleared crude (JCC) because of the liquidity and transparency of crude oil prices and the substitutability of natural gas and petroleum products in certain markets [EIA, 2015].

Numerous locations in Asia, including coastal China, Japan, Taiwan, South Korea, are particularly dependent on more expensive LNG because there are limited regional natural resources of economic natural gas. Further, the interrelated nature of current crude oil and natural gas markets in Asia means that a supply shock affecting crude oil markets also affects the natural gas markets in Asia. Therefore, forecasting methods must address the interrelated nature of different energy products.⁴

As a result of the substantial reductions in crude oil prices beginning in late 2014, LNG prices in Asia also showed reductions. Figure 4 shows the recent historical trends in prices of LNG delivered to Japan. Numerous market-related factors affected supply and demand over this extended period, and there was substantial impact from macro-economic related factors as well.

Major energy forecasts of LNG prices are completed by government agencies and are mostly produced from the large-scale simulation tools they use to replicate the market function under a variety of scenarios to depict the future of the energy sector. For example, the International Energy Agency (IEA) conducts a World Energy Outlook which includes three primary modules to represent the economic characteristics of future energy consumption (by sector for industry, transport, building and agriculture and non-energy use), energy supply (fossil fuel and bioenergy) and energy transformation (power, heat generation, oil refining and others). The primary outputs from the model for each region are energy demand, supply by fuel and investment needs as well as CO₂ [IEA, 2014].

uses in feedstock and process applications. A new manufacturing renaissance has already begun, as petrochemical and other projects have been announced to take advantage of these recent natural gas industry benefits.

⁴To the extent that new market approaches are developed for natural gas, these would need to be incorporated into the forecasting methodology. For example, while long-term crude oil-indexed contracts have been Asia's dominant pricing mechanism, to the extent that natural gas trades on the spot market as one-time transactions, or under short-term contracts which more closely reflect international natural gas supply and demand balances becoming more prominent, forecasting methodology will need to reflect the underlying economic conditions.

Fig. 4. Historical LNG Japan prices (\$/MMBTU).

Notes: The declines in Japan LNG largely track the Brent crude oil prices as well as the observed price declines in Brent crude oil and relatively stable trend of the US regional Henry Hub natural gas price index.

Source: Bloomberg, LNGJLNP Index-Closing Price.

The recent declining trends in LNG prices have impacted the IEA's forecast of LNG prices. In the 2014 forecast, the IEA forecasted an approximately \$14/mmbtu price for LNG delivered to Japan in 2020 in its New Policies Scenario [IEA, 2014]. In the 2015 forecast, the IEA reduced its forecast price for LNG delivered to Japan to \$12.2/MMBTU price [IEA, 2014]. As discussed above, the interrelated nature of current crude oil and natural gas markets in Asia requires forecasting methods to address the interrelated nature of different energy products.

2.5. Electricity

Over the past three decades, electricity markets in the US and many international countries have progressed from a fully rate-regulated regime to wholesale deregulated electricity markets and to some extent deregulated markets. The historical context of deregulation is helpful to put today's challenges into perspective.

In the US, the Energy Policy Act of 1992 [IEA, 2014] was a significant step that allowed for more competition in the electricity industry. Among other changes, this Act allowed electricity to be sold at market prices, as opposed to a heavily regulated rate, and allowed for unregulated firms to independently buy and sell electricity on the open wholesale market. This greatly increased the incentives for trading. It also provided for a new category of market participants, electric power marketers.

Marketers were allowed to buy and sell electricity at whatever price the market would bear, similar to traders of stocks on Wall Street or traders of commodities on the Chicago Board of Trade.

The regulatory responsibility for implementing these changes fell to the Federal Energy Regulatory Commission (FERC). FERC issued orders in 1996 that required utilities to make their transmission systems available to others to move electricity and reach customers, and the detailed rules providing for these changes were adopted in 1998 [FERC, 2010]. Systems with independent system operators, such as PJM, New York and New England, were well positioned to create open markets for electricity. In late 1999, FERC issued an order that provided incentives for the utilities it regulates to join newly-defined Regional Transmission Organizations, or RTOs [FERC, 1999]. The RTOs would support increased trading and could decide to take the further step of becoming independent system operators, but there was no requirement for utilities to join RTOs, nor for RTOs to take on the full responsibility of becoming independent system operators. When not required, many RTOs have been formed and the shift toward increased independent system operators continues to this day. Even without the independent system operator function, RTOs have helped improve the efficiency of the markets by supporting competitive market structure, lowering the cost of moving electricity over longer distances.

Meanwhile, states took action to promote more competitive retail electricity markets, with considerable variation among the actions taken at the state level. State laws called for a fundamental restructuring of the industry in, for example, California [EIA, 1998] and Texas [EIA, 2014]. Provisions allowing for retail competition, where homeowners and other customers could decide which supplier they wanted to provide energy to (which would be transmitted to their homes on their traditional utility's wires), were adopted in many states [DOE, 2007]. At the wholesale level, it became easier for private companies that were not subject to sell-at-cost-based state regulation to build power plants and sell their electricity at market prices. The old system of vertically integrated utilities has been breaking down, particularly with increased competition among electricity generators.

Fast forward to today, the US has continued to develop wholesale power markets but new challenges have emerged. The lower commodity prices of natural gas, resulting from the abundant shale gas resources, has put downward price pressure on natural gas which has led to price reductions of power as well. Lower market-clearing prices for power result because the lower natural gas fuel costs substantially lower the short-run marginal cost (SRMC) of natural gas-fired power plants because fuel costs comprise the majority of the SRMC. Further, natural gas power plants have historically been the marginal power plant that set the overall market-clearing

price where total supply equals total demand for power in a geographic market for a specific time period. The lower market-clearing prices for power have raised concerns of financial adequacy of power generation facilities, such as nuclear, coal and natural gas plants. In addition, rapid integration of intermittent renewable resources, particularly wind that is generated at almost zero cost, raised grid reliability issues [Deng *et al.*, 2015; Dillig *et al.*, 2016]. These shifting supply-side market dynamics create uncertainty and additional risks. Further, slower growth in the demand for power than historically observed has further depressed the market-clearing prices for power and created additional demand-side market-based risks [EIA, 2016].

2.6. Renewable, emerging technologies and energy efficiency and climate policy

The domestic and global energy industry is inextricably linked to political and regulatory systems that collectively implement government objectives for the energy industry, including economic incentives for investment and regulatory oversight. We will use the US state REC prices to understand the impact of federal policy on the future prices of RECs employing time series forecasting methods in Section 4.1.

In recent years, increased US regulatory intervention and requirements associated with environmental policy goals have created preferences for heavier reliance on cleaner sources of energy. US Regulatory and policy initiatives have increased and are expected to further increase the demand for renewable power and, to some extent, natural gas-fired power plants (which is the lowest CO₂ emission fossil fuel). Specifically, Energy Policy Act of 2005 fostered renewable energy investments, including wind and solar energy, through tax incentives, such as Production Tax Credits (PTC) and Incentive Tax Credits (ITC), which drove the increasing demand and supply of renewable energy investments [Bolinger *et al.*, 2009]. The PTC policy provides financial compensation on a unit of output basis (dollar per kWh) of wind generation produced during the first 10 years of operation. Wind capacity installations have grown substantially across the country with the support of federal incentives [Eryilmaz *et al.*, 2016]. In addition to the federal support, US states have initiated various incentives for renewable energy generation. Renewable Portfolio Standards (RPS) is one of the most well-known energy regulatory mandates specifically designed to increase production of renewable energy generation. This policy requires a certain percentage of electricity generated from renewable resources (e.g. 20% of electricity generated from renewable resources by 2020). The application and achievement goals of RPS policies are distinct for every state.

Although the implementation and the required goals vary in each state, the common goal of these standards is to develop a REC market. RECs are tradable commodities that reflect the environmental attributes of electricity being produced and credits are earned with the production of renewable electricity that are also used to comply with the RPS mandates. RECs that are administered in the compliance market receive a unique tracking number from the state agency (e.g. MRETS in Minnesota) and they can be traded in the RECs market among the generators and utilities [Heeter *et al.*, 2011]. In other words, a qualified generator can produce and sell RECs to retailers or retailers can buy RECs from a utility that has excess amount of RECs due to overproduction. Although RECs provide incentives for the renewable energy generators, price uncertainties in the RECs market affect the renewable electricity sector [Fell *et al.*, 2012].

An additional and recent policy is the state-level policy surrounding Net Energy Metering (NEM). NEM is the state-level incentive specifically for distributed generation, referred to as behind-the-meter because it resides at customer locations. The NEM policy enables residential solar consumers to generate solar electricity for their own consumption and to be able to sell excess amount of electricity generated back to the wholesale power grid and to be compensated for the sale of the excess power generation [EEI, 2016].

These policies have promoted the integration of renewable resources, particularly in power generation. The intermittent nature of renewable power (i.e. only when the sun shines or the wind blows) and limited energy storage capabilities make forecasting renewable energy more challenging [Hong, 2014]. The difficulties in accurately predicting wind and solar generation is one of the biggest challenges in renewable energy forecasting. It becomes particularly more challenging because of the wide geographical distribution of these resources and unpredictable nature of their share in the electricity generation mix. To give an example, wind generation during times when the grid is congested (i.e. when energy generation is more expensive) is a more cost-effective resource for the generators. However, wind is intermittent and it is highly uncertain to predict the cost of generation from this resource during grid congestion. On the other hand, large amount of electricity generated from distributed solar energy during times when the electricity demand is low may result in extremely low voltage, which could create reliability issues at the feeder level of the transmission network [Palminier *et al.*, 2016].

Tremendous research and development has occurred and continues, and the predictability of the changes and the order of magnitude on impact and timing are not easy to anticipate. All of these technological developments have created discussions

about the appropriate utility regulation and business model going forward to meet the future energy needs under policy and market uncertainty.

3. Applied Methods for Forecasting Energy Markets

3.1. Energy demand

Changing policy and regulations in energy has been one of the important drivers of the changing trends in energy demand. In fact, policy is not the only factor that influences energy demand. Choice theory in traditional economics is the foundation of demand for economic matters, such as consumption, investment and savings. In energy economics literature, energy demand is also based on traditional economic utility theory. Traditional economic theory suggests that price of a good is the main driver of its demand. Therefore, economists have conducted extensive research to understand the relationship between energy demand and energy prices.

Demand for energy resources has been widely studied in applied research. Early research by Deaton [1974], Houthakker [1970, 1974] and Bohi and Zimmerman [1984] have demonstrated the dynamic nature of energy demand. Further, predicting future demand is critical for planning the allocation of resources and meeting energy needs of future generations.

Demand for energy is mostly derived from the demand for energy services, such as oil for transportation, natural gas and electricity for lighting, heating and cooling [Platchkov and Pollitt, 2011]. The utility function of an economic agent (i.e. household and businesses) includes the energy services and the economic agent maximizes its utility subject to its budget constraints. Equation (1) illustrates the utility maximization problem of the economic agent i .

$$\max_{\{e_i\}} u_i(e_i) = \max \prod_{i=1}^N e_i^{(a_i)} \text{ subject to } y_i = \sum_{i=1}^N p_i e_i \quad (1)$$

The solution of the utility maximization problem yields a demand function that is a function of income (y) and energy prices (p_1, p_2), as shown in Eq. (2) [Mas-Collel *et al.*, 1995; Levin and Milgrom, 2004; Alberini and Flippini, 2011],

$$e_i^* = f(y_i, p_i) \quad (2)$$

For the sake of simplicity, we assume Cobb–Douglas functional form (i.e. linear) throughout this chapter. We define demand model in Eq. (3), where e_i represents the energy demand for economic agent i , P_i represents energy prices, Y_i represents income, X_i represents other factors affecting energy demand such as Gross Domestic

Product (GDP) or home size of an household and finally, ε_i is the identically and independently distributed error term. In this econometric regression equation, a_0, b_1, b_2 and b_3 are the estimated coefficients to predict energy demand.

$$e_i = a_0 + b_1 \cdot P_i + b_2 \cdot Y_i + b_3 \cdot X_i + \varepsilon_i \quad (3)$$

Considering the dynamic nature of the energy demand, the model specification adjusts for the short-term and long-term response to income and price changes. In the case of energy users who are unable to adjust instantly for the optimal amount of energy consumed due to production or technological constraints, Eq. (4) accounts for this adjustment with $e_{t-1,i}$ and the estimated coefficient b_4 is the adjustment factor to the optimal energy demand based on the actual demand.

$$e_{t,i} = a_0 + b_1 \cdot P_{t,i} + b_2 \cdot Y_{t,i} + b_3 \cdot X_{t,i} + b_4 \cdot e_{t-1,i} + \varepsilon_{t,i} \quad (4)$$

Depending on the research focus and study objectives, model specification can be modified [Bhattacharyya and Timilsina, 2009]. For example, this modeling framework can also account for regional variation, home size or seasonality. In Section 3, we provide concrete application of this modeling framework with the examples from the energy industry.

3.2. Energy supply

Energy supply is also primarily driven by the energy prices [Fezzi, 2007]. The law of supply suggests that an increase in price of a good leads to an increase in the quantity offered (or supplied) of that good. The energy supplier solves the profit maximization problem that is shown in Eq. (5) to produce a given amount of energy [Varian, 1992; Jebaraj and Iniyar, 2006],

$$\max_{\{e_j\}} \Omega_j(e_j) = \max \sum_j^N p_j e_j \text{ subject to } m_j = f(e_j). \quad (5)$$

The solution of the profit maximization problem yields a supply function that is the function of units of output (m_j) and energy prices (p_j), as shown in Eq. (6),

$$e_j^* = f(e_j, w_j). \quad (6)$$

Another way of expressing the energy supplier's problem is the cost minimization such that the supplier produces a certain amount of energy with the least cost. Equation (7) shows the minimization problem, where e_j is the amount of inputs needed to produce m_j quantity of energy, q_j is the input prices for energy production

(e.g. technology, labor, water) that is subject to the quantity of energy to be produced m_j .

$$\min_{\{x_j\}} C_j(x_j) = \min \sum_j^N q_j x_j \text{ subject to } m_j = f(x_j). \quad (7)$$

In this case, the solution of the minimization problem yields the conditional demand equations where e_j becomes a function of input prices to produce energy and the total output of energy as shown in Eq. (8):

$$e_j^* = f(x_j, m_j). \quad (8)$$

3.3. Overview of general equilibrium

After deriving energy demand and energy supply, market equilibrium can be defined as the point where the amount of energy demanded is equal to the amount of energy supplied in a competitive energy market. A competitive energy market can be defined as the economic agents are price-taking, meaning that individual economic agents cannot directly influence the market price, as shown in Eq. (9).

$$\sum_i^N e_i^*(p) = \sum_j^M e_j^*(p) \quad (9)$$

There is a significant amount of research on general equilibrium modeling using numerical methods. In this chapter, we focus on partial equilibrium analysis using empirical methods while encouraging readers to explore structural models and applications in computational general equilibrium models (CGE) from General Trade Analysis Project (GTAP) by Purdue University and the relevant resources.

4. Case Study

4.1. An example from renewable energy market: Forecasting REC prices

The relationship between renewable energy policies has received little attention of researchers. In this example, we evaluate the interaction between these two renewable energy policies in the US: federal PTC and the market for RECs from state RPS policy. This example provides a forecast for the movement of the future RECs prices along with the changing commodity prices under the changes in federal policies. It is important to understand the impact of the federal PTC policy on state policy is because the PTC policy was set to be retired by the federal government several times in the past. The decision by the federal government had implications on renewable energy every time it announced to retire and enact the policy. Table 1

Table 1. Legislative history of PTC policy.

Date announced	Duration	Effective duration
08/08/2005	24 months	01/01/06–12/31/07
12/20/2006	12 months	01/01/08–12/31/08
10/03/2008	12 months	01/01/09–12/31/09
02/17/2009	24 months	01/01/10–12/31/12
01/02/2013	12 months	01/02/2013–12/31/2013

Note: Most recently, the PTC pays for the renewable energy investors 2.2¢/kWh for wind and geothermal resources and 1.1¢/kWh for other renewable resources (PTC is adjusted to the inflation over time).

Source: Lou (2011) and Wiser *et al.* (2007).

provides the legislative history for the PTC policy. As shown in the table, this policy was announced at a certain date and had an effective time period. After the time period ended, the government had an option to enact the policy again or retire it completely. This created uncertainty in the renewable energy markets because the investors who rely on the federal incentive were unsure whether their investment was going to be subsidized due to the uncertainty in the policy.

RECs are market-based and PTC policy is a price-based policy (i.e. subsidy paid per MWh generation in the next 10 years of investment) for increasing the supply of the renewable energy. However, there is uncertainty about the future renewable energy policies (i.e. REC market and PTC) after mandatory requirements are met. Understanding the impact of this federal policy as well as the relationship between state and federal policies is important for forecasting and future decision-making. Moreover, PTC is a federal tax program, whereas the RPS which generates the market for RECs are at the state level. Therefore, identifying the interaction between the state-level and the federal-level policies are important since the design of these policies is different in terms of cost paid by the government. This example evaluates the policy and the impact of the federal policy on future REC prices. We also test the causal short-term impact of electricity prices on the RECs prices based on historical time series data.

Data are obtained from the EIA and the MarexSpectron Company. Our data include the daily spot prices for the national REC market and the spot prices for the electricity prices. The REC market data include daily historical data on both the compliance and the voluntary⁵ market bid and offer prices. We only used the compliance market data for this analysis. We also contracted a policy variable based

⁵Compliance Markets for RECs: RPS goals drive the RECs trading, utilities and the power-generating companies to buy and sell RECs to meet their state-level requirements. Voluntary Markets for RECs: Consumers and institutions purchase renewable energy on a voluntary basis [Heeter and Bird, 2011].

on our knowledge on when the government announced the PTC and when the PTC is set to expire. Therefore, a dummy variable (i.e. a 0/1 variable) will be generated based on this historical information. Table 1 summarizes the legislative history of the PTC policy.

Table 2 provides the descriptive statistics of our data and Fig. 5 includes the historical daily prices for the REC compliance and voluntary markets.

We used time series data for two regions that have a market for RECs, PJM and NEPOOL, where the average daily prices differ across the regions. Regional REC markets cover multiple states. The PJM region includes the trading states: Delaware,

Table 2. Descriptive statistics for the market price data May 2006–November 2012.

Region	Wholesale electricity prices (\$/MWh)	REC prices (\$/MWh)
NEPOOL	62	32
PJM	58	86

Note: All variables are in daily format.

Fig. 5. Daily REC prices.

Ohio, Maryland, New Jersey, Pennsylvania, Texas and Washington D.C. NEPOOL region includes the trading states: Massachusetts, Maine, New Hampshire, Rhode Island and Connecticut. PJM region had the highest average REC prices (\$86/MWh) and NEPOOL average prices were (\$32/MWh).

Prior to developing a forecasting model with any time series data, we need to determine whether it is suitable for forecasting. More specifically, in order to proceed with the analysis, we need to determine whether price series are “stationary”. By definition, stationary time series is defined as the series with constant mean, variance and autocorrelations can be well approximated by sufficiently long time averages [Enders, 2010].

As a first step, we plotted the actual spot prices and the lagged REC prices as in Fig. 5. After visually inspecting the data series, we see that daily REC prices are fluctuating between 2006 and 2012; however, there is a downward trend in the last couple of years. Visual assessment of the price series is useful but not sufficient to determine stationarity. Therefore, we need to employ formal statistical tests. Dickey–Fuller and KPSS tests are the most commonly used statistical tests for stationarity. The null hypothesis for Dickey–Fuller test statistic is that “the time series is non-stationary”. It essentially tests whether the relationship between the time series and its lags are statistically significant (i.e. tests whether the coefficient δ is statistically different from zero in equation

$$y_t = a_0 + \delta y_{t-1} + \varepsilon_t. \quad (10)$$

We present the results for Dickey–Fuller test, as shown in Table 3. We found that REC prices are non-stationary because the Dickey–Fuller test statistic is not sufficiently greater than the p -value [Wooldridge, 2009; Brockwell and Davis, 1986]. In addition, the test statistic was not sufficiently greater than the 1%, 5% or 10% critical value, suggesting that the series is non-stationary. We also tested whether the REC prices are trend stationary, have a drift (i.e. constant term) and whether there is a significant dependency on the lagged values. We found that the estimated coefficients on trend, constant and lagged REC prices are statistically different from zero, except for the second lag of REC prices in PJM. The estimated coefficients are also presented in Table 3.

The most common method to convert non-stationary data into stationary data is differencing (i.e. $\Delta y_t = y_t - y_{t-1}$). Although differencing converts the data into stationary, stationary data from the first differencing also eliminates the information about the causal effects of the federal policy in such frequent time series data. The differenced data are stationary, but we cannot estimate the change in the slope or the intercept of the time series based on policy intervention. Therefore, we have used

Table 3. Dickey–Fuller Test Statistic for REC prices.

Region	Dickey–Fuller test statistic	1% critical value	5% critical value	10% critical value	<i>p</i> -value
NEPOOL	−1.183	−3.960	−3.410	−3.120	0.9139
PJM	−1.243	−3.960	−3.410	−3.120	0.9013
		NEPOOL		PJM	
REC [t−1]	−0.006 (−1.18)			−0.0072 (−1.24)	
REC [t−2]	−0.027 (0.037)			−0.123** (−2.73)	
Trend	0.00003 (0.0001)			−0.00004 (0.0002)	
Constant	0.212 (0.162)			0.906 (0.504)	

Notes: *t*-statistics in parenthesis. **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

Fig. 6. Daily detrended REC prices.

Hodrick–Prescott smoothing method, which is a common method to remove trend movements in non-stationary time series data in business cycle literature [Baum, 2006]. The detrended series and the historical prices are shown in Fig. 6.

Using the detrended data, we now introduce the policy intervention, the federal PTC policy and see whether there is an effect of the policy on the REC market. These policy decisions are often perceived as shocks to the market and we test

whether the changes in policy intervention have an impact on REC market prices.⁶ The most recent PTC expiration was set for December 2012 and in early January 2013, the policy was reactivated until January 2014. We define “intervention” as the time when the federal policy is announced to be effective (i.e. no time lapse in the PTC policy and investors are certain they will receive the tax credits), which makes it a dummy variable that takes the values of “1” for the associated month and takes the value of “0” in the remaining days. We are interested in the effect of the PTC policy on the REC market prices.

Federal government announces the day that the PTC will be effective and the day it will expire. PTC was announced and expired many times in the past, therefore we divided the historical price data into two different time segments and included the continuous “time” variables, into the regression: t is a continuous time variable, which takes the time values where the PTC is not announced. When $PTC_t = 1$, we estimate $\hat{\alpha}_2$ which denotes the time that the PTC is effective. We estimate the following linear equation with Ordinary Least Squares (OLS) approach, which is a method to predict an outcome variable by minimizing the sum of squared errors.⁷ We also included the time trend and an indicatory variable taking value 1 for the associated month of a year and otherwise 0. The monthly dummy (i.e. indicator) variables control for the seasonality and the unobserved time effects associated to each month on REC prices.

$$\log(REC_t) = \alpha_o + \alpha_1 PTC_t + \alpha_2 t + \sum_i^{12} \alpha_{3,i} \text{Month}_t + \varepsilon_t \quad (11)$$

Our results are shown in Table 4. The estimated coefficients on the policy variable (PTC_t) are positive and highly significant for each region, indicating that after the announcement of the continuation of the policy intervention, REC prices are higher. More specifically, compared to the REC prices in NE, it is approximately 0.02% higher and PJM is approximately 0.017% higher after the federal government announced that the PTC policy will be continued. This could be explained by the increase in the supply of renewable electricity with the incentives offered to the investors. We have tested the change in slope as well as the change in the intercept using standard t -tests. Based on the regression results, we can conclude that the estimated coefficients are significantly different from zero, which suggests that there are differences in the REC price market before and after the “event”. Moreover,

⁶This method is also known as Interruptible Time Series, which predicts the impact of a policy intervention in high-frequency time series data.

⁷For more detailed information about this modelling approach, see Wooldridge [2009].

Table 4. Estimations results.

Variable	NEPOOL	PJM
PTC_t	0.0208*** (0.00124)	0.0169*** (0.000831)
$t(trend)$	0.00000568 (0.00000348)	0.00000287* (0.00000126)
2 month	0.0975* (0.0414)	0.0427 (0.0453)
3 month	0.114** (0.0420)	0.0503 (0.0453)
4 month	0.163*** (0.0443)	0.0797 (0.0447)
5 month	0.0961 (0.0536)	0.061 (0.0440)
6 month	-0.125 (0.0657)	0.0466 (0.0425)
7 month	-0.123* (0.0585)	0.0239 (0.0429)
8 month	-0.121* (0.0550)	0.00319 (0.0442)
9 month	-0.0902 (0.0524)	-0.0332 (0.0460)
10 month	-0.0365 (0.0494)	-0.0265 (0.0481)
11 month	0.00333 (0.0510)	-0.0105 (0.0489)
12 month	0.0254 (0.0503)	0.0523 (0.0475)
Constant	10.03*** (0.0324)	11.10*** (0.0352)
N	2374	2374

Note: REC prices are in natural logarithm form and the values presented in the brackets are standard errors.

these results suggest that the detrended series are stationary and still include the information of interest.

Note that the intervention (i.e. PTC_t in this example) could have been defined differently based on the researcher's interest such as taking the value 1 during the lapse period. Additionally, effects of different interventions (i.e. effect of government announcing period, lapse period and effective period) could have been tested in the same model specification as well. We presented the simplest model as a reference. An important assessment, which we did not discuss in this chapter, is the assessment of the autocorrelation, which is the delayed correlation of a

Fig. 7. REC prices and electricity prices in NEPOOL and PJM regions.

given series. We recommend Enders [1995] as an invaluable resource for further information.⁸

4.2. Vector Autoregression model

The second empirical method that will be employed in this study is the Vector Autoregression (VAR) model. VAR models are mostly used with the time series data that are stationary to understand the dynamic relationship between the two series [Enders, 1995]. In this example, we examine the future relationship between REC prices and electricity prices in NEPOOL and PJM as well as the causal impact of PTC policy on the REC prices.

The VAR method allows us to answer the question: Does existence of PTC cause decrease/increase on the prices of the market for RECs in the future given there are other markets affecting the RECs prices? Granger causality test will be applied to test for the future causal relationship between the policy of PTC and the RECs [Enders, 1995]. A potential limitation of this approach could be the identification

⁸An example alternative specification could be

$$\log(REC_t) = \alpha_0 + \alpha_1 \log(REC_{t-1}) + \alpha_2 PTC_t + \alpha_3 t + \sum_{i=1}^{12} \alpha_{4,i} \text{Month}_t + \varepsilon_t.$$

problem and the strong assumption that announcing PTC is the primary shock for the REC market, whereas there can be other potential shocks that are omitted from the analysis — that could be tested in future research (e.g. economic recession and level of renewable energy investments decrease significantly or there is a sudden high amount of purchase/sell in the REC market). We define a system for both REC and electricity prices, where REC price series can be affected by the current or lagged values of the electricity prices, or vice versa. Equation (11) presents the estimated VAR model. As shown in the equation, we specify REC prices as a function of its lags and the electricity prices while the electricity prices are specified as a function of REC prices, lagged electricity prices. To ensure stationarity, we take the first difference of the REC and the electricity prices for VAR analysis. We tested the differenced series with Dickey–Fuller test and confirmed that both the first difference of electricity and REC price series result in stationary series.

$$\begin{aligned}\Delta REC_t &= \alpha_{10} + \alpha_{12} \Delta REC_{t-1} + \alpha_{13} \Delta Elec_{t-1} \\ \Delta Elec_t &= \alpha_{20} + \alpha_{21} \Delta Elec_{t-1} + \alpha_{22} \Delta REC_{t-1}\end{aligned}\quad (12)$$

The results from VAR analysis include estimated coefficients for the variables specified in Eq. (11) and presented in Table 5.

We found that the regional electricity prices in NEPOOL influence future REC prices and the estimated coefficient is statistically significant at 95% significance level. More specifically, a dollar increase in wholesale electricity prices in NEPOOL

Table 5. Estimations results.

	NEPOOL	PJM
Equation 1: REC		
$\Delta REC [t-1]$	-0.03 (-0.02)	-0.174*** (-5.10)
$\Delta Elec [t-1]$	-0.0133* (-2.43)	-0.0107 (-1.15)
Constant	0.035 (0.59)	0.10 (0.84)
Equation 2: Electricity		
$\Delta Elec [t-1]$	0.0268 (0.76)	0.0304 (0.06)
$\Delta REC [t-1]$	0.188 (0.81)	0.131 (1.01)
Constant	0.177 (0.65)	0.43 (0.96)
Number of Observations	908	934

Notes: *t*-statistics in parenthesis. **p* < 0.05, ***p* < 0.01, ****p* < 0.001.

is associated with a cent decrease in future REC prices. Similarly, a dollar increase in PJM wholesale electricity prices is associated with about one cent decrease in REC prices in PJM. We found that there is no significant impact of REC prices on the wholesale electricity prices. This could be explained by the fact that REC market is not large enough to influence the prices in the wholesale electricity market.

We assumed that the first lag of prices is appropriate for this VAR model, however, in order to compare the model goodness-of-fit, we recommend using Akeike Information Criterion (AIC) and/or Bayesian Information Criterion (BIC) [Gujarati and Porter, 2009] to select between competing models.

One of the primary outcomes of the VAR model is impulse-response function, which illustrates the direction and significance of the future relationship between the REC and electricity prices using the estimated coefficient from Eq. (11). The confidence intervals in the impulse-response function are created using the standard errors of the estimated coefficients. These impulse-response functions show that the impact of electricity prices on REC prices is short term, i.e. the next 1–5 days depending on the region. Figure 8 presents the impulse response function between REC and electricity markets in both NE and PJM regions. This figure illustrates the short-term future relationship between REC prices and electricity prices. In this specific example, we considered the 10-day forecast and we see that the increase in REC prices is associated with an increase in the electricity prices. Remember that we used the first difference of the REC and electricity price series that are stationary, and the observed shock prices will not be persistent. When the impulse is the regional REC prices, the response of the electricity prices is positive the next day for PJM, but then the response goes down to zero indicating there is no impact after a day. For NEPOOL, the response of the electricity prices is fluctuating for the following 5 days, where we see a positive response on the second and fourth days, while response is negative on the next and third days. These impulse-response functions show the short-term impact of electricity prices on REC prices, i.e. for the next 1–5 days, depending on the region. These graphs are produced using Stata software, and they include the 95% confidence intervals, as shown in the figures.

This practical exercise helps us understand the statistical relationship between the REC prices and electricity prices in the near future. Findings suggest that the policy interventions have an impact on the REC market prices. Changes in policy decisions and government actions on policy announcements influence the markets. Further, renewable market is highly affected by the wholesale electricity prices in the short term. This short-term relationship is important to understand as more renewables are being integrated in the system and the causal relationship between the electricity prices. However, long-term relationship between the REC prices and

Fig. 8. Impulse response functions.

electricity prices are kept outside the scope of this analysis and deserves attention in future research. Consequently, this study should be expanded with additional model specification testing in order to derive specific policy recommendations. As our purpose is to illustrate the basic steps to analyze time series data for short-term

forecasting with this exercise, we do not draw any policy conclusions from this analysis.

5. Concluding Remarks

This chapter covers the evolution of market dynamics for multiple energy markets, including crude oil, natural gas, electricity and renewables. We provide an overview of markets for these energy sources and challenges for forecasting prices or quantities with changing market dynamics. Understanding these markets is the key for employing the appropriate forecasting methods that can provide the most accurate and reasonable results for decision- and policy-making efforts and we aim to provide this knowledge to the readers in this chapter.

We would like to conclude by highlighting that the objective of the practical example is mostly illustrative. Note that there are many alternative specifications available and also options for the number of lags that can be utilized. Statistical fit should provide guidance and appropriate statistical tests should be completed to ensure a robust and reliable model. Therefore, our examples in this chapter serve as an illustration of fundamentals of these discussed methods and similar research questions should not limit their analyses to the approaches and statistical tests presented in this chapter.

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