- Student Name: Lisa Arends
- Student pace: full time
- Instructor: Claude Fried
- Blog post URL: https://fromteachingtotech928923879.wordpress.com/2021/10/01/who-buys-the-wine-using-clustering-for-market-segmentation/ (https://fromteachingtotech928923879.wordpress.com/2021/10/01/who-buys-the-wine-using-clustering-for-market-segmentation/)

1 Problem Statement

GA Power is the largest power utility in Georgia, serving over 2.3 million residential customers. A net-metering program was initiated in 2019 that allowed customers with photovoltaic (PV) solar panels on their roof to sell excess electricity to GA Power at competitive rates. The cap of 5,000 customers for the program was recently reached, disincentivizing customers from installing solar power on their homes.

1.1 Business Value

Eliminating the net metering cap will incentivize more Georgia residents to install PV panels on their homes because they will be able to sell back their excess electricity at competitive market rates, thus decreasing the time it takes for the system to pay for itself. Increasing the number of homes with PV solar panels will benefit the residents of Georgia by helping to moderate energy prices and limit demand on the grid. Furthermore, an increase in residential PV systems will position the state to be more resilient in the face of a changing energy landscape and will ensure that Georgia remains competitive in the U.S. energy market.

1.2 Questions to Consider

- How will Georgia's dependence on imported electricity change in the coming years?
- How are natural gas prices expected to change and how will that impact Georgia's fuel costs?
- What is the correlation between extreme temperatures and the demand on the residential electrical grid?
- How does Georgia's per capita production of solar from residential systems compare to the U.S.?

1.3 Methodology

Data from the U.S. Energy Administration(EIA) were used to analyze the trends and forecast future changes in Georgia’s residential power demand, natural gas prices and residential solar generation. In addition, the relationship between extreme temperatures and demand on the electrical grid was investigated.

2 Obtain the Data

In [1]:
```
import pandas as pd
import numpy as np
import requests
from bs4 import BeautifulSoup
import joblib
from joblib import dump, load
import os

import statsmodels.api as sm
from statsmodels.tsa.stattools import adfuller
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.formula.api import ols
from statsmodels.stats.stattools import durbin_watson

from sklearn.metrics import mean_squared_error
from sklearn.linear_model import LinearRegression
from sklearn.dummy import DummyRegressor
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import cross_validate
from sklearn.model_selection import cross_val_score
from sklearn.pipeline import Pipeline

from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import LSTM, Dense, Flatten, Bidirectional
from tensorflow.keras import regularizers
from keras.preprocessing.sequence import TimeseriesGenerator
from keras.callbacks import EarlyStopping

from scipy import stats

from datetime import datetime
from datetime import timedelta

import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

%matplotlib inline

sns.set_style('darkgrid')
sns.set_context('talk')
NEUTRAL = '#5f8195'
HIGHLIGHT = '#00c3b1'
DARK_NEUTRAL = '#3d3d3d'
LIGHT_NEUTRAL = '#dff2f7'
BRICK = '#b45f06'
MEDIUM = '#7aa3ad'
GREEN = '#64be3c'
PALETTE = 'deep'
```

executed in 5.51s, finished 09:18:13 2021-10-22

2.1 Reduce Dependence on Imported Electricity

Use forecast of number of future customers and percent of electricity used in Georgia that is imported from other states to show how dependence on outside resources will increase, putting Georgia in a potentially vulnerable position.

In [2]:
```
#From EIA.gov; Number of residential electricity customers from 2008-2021.
#measured monthly
ym_parser =  lambda x: datetime.strptime(x, "%Y%m")
customers = pd.read_csv(
    'files/number_customers_monthly.csv',
    skiprows=6,
    parse_dates=['Source'],
    date_parser=ym_parser,
    index_col='Source'
)
customers.columns = ['number_of_residential_customers']
customers = customers.sort_index()
customers.index.freq = 'MS'
customers.head()
```

executed in 17ms, finished 09:18:13 2021-10-22

Out[2]:

Source	number_of_residential_customers
2008-01-01	4018970
2008-02-01	4025567
2008-03-01	4028445
2008-04-01	4028785
2008-05-01	4033126

In [3]:
```
#From EIA.gov; The amount of electricity in GA from various sources from
#1960-2019, measured annually, in billion btus.
cols_to_use_source = ['Series Key', 'SEDS.RETCB.GA.A', 'SEDS.PMTCB.GA.A',
        'SEDS.NUETB.GA.A','SEDS.NNTCB.GA.A','SEDS.CLTCB.GA.A',
        'SEDS.TETCB.GA.A','SEDS.ELISB.GA.A']
by_source = pd.read_csv(
    'files/ga_annual_by_source.csv',
    usecols=cols_to_use_source,
    )[6:]
by_source.columns = (
    ['date',
     'renewable',
     'petroleum',
     'nuclear',
     'natural_gas',
     'coal',
     'total',
     'imported'])
by_source['date'] = pd.to_datetime(by_source['date'], format='%Y')
by_source = by_source.set_index('date')
by_source = by_source.astype(float)

#Add a column to track the % of electricity that is imported
by_source['percent_imported'] = by_source['imported']/by_source['total']
by_source.head()
```

executed in 22ms, finished 09:18:13 2021-10-22

Out[3]:

date	renewable	petroleum	nuclear	natural_gas	coal	total	imported	percent_importe
2019-01-01	313981.0	1007518.0	350759.0	787386.0	273109.0	2963080.0	230327.0	0.07773
2018-01-01	303411.0	1009846.0	359262.0	759205.0	340152.0	3010509.0	238634.0	0.07926
2017-01-01	293453.0	1038950.0	352560.0	709671.0	344273.0	2933159.0	194252.0	0.06622
2016-01-01	298083.0	983632.0	360633.0	727336.0	399279.0	2959871.0	190908.0	0.06449
2015-01-01	300816.0	1008952.0	353883.0	712580.0	394665.0	2985813.0	214917.0	0.07197

2.2 Mitigate Impact of Rising Natural Gas Prices

In [4]:
```
#From EIA.gov; Natural gas futures for 1994-2021, measured daily, in dollar
# per million btu units

cols_to_use = (
    ['Series Key',
     'NG.RNGC1.D',
     'NG.RNGC2.D',
     'NG.RNGC3.D',
     'NG.RNGC4.D']
)
gas_price = pd.read_csv(
    'files/natural_gas_daily_price.csv',
    usecols = cols_to_use)[6:]
gas_price = gas_price.dropna()
gas_price["Series Key"] = pd.to_datetime(
    gas_price["Series Key"],
    format='%Y%m%d')
gas_price = gas_price.set_index('Series Key')
gas_price = gas_price.astype(float)
gas_price['avg_price'] = (
    gas_price.iloc[:,0]+
    gas_price.iloc[:,1]+
    gas_price.iloc[:,2]+
    gas_price.iloc[:,3])/4

gas_price = gas_price.drop(
    ['NG.RNGC1.D',
     'NG.RNGC2.D',
     'NG.RNGC3.D',
     'NG.RNGC4.D'],
    axis=1)
gas_price.head()
```

executed in 37ms, finished 09:18:13 2021-10-22

Out[4]:

Series Key	avg_price
2021-10-05	6.41825
2021-10-04	5.88975
2021-10-01	5.74425
2021-09-30	5.97050
2021-09-29	5.57675

2.3 Decrease Strain on Power Grid During High Demand Periods

In [5]:
```
# From EIA.gov; demand in mwh measured hourly from 2015-2021; measurements
# are for the Southeast region, in mwh
cols_to_use_reg = ([
    'Series Key',
    'EBA.SE-ALL.D.H',
    'EBA.TVA-ALL.D.H'
])
regional_demand = pd.read_csv(
    'files/regional_demand.csv',
    usecols=cols_to_use_reg)[6:]
regional_demand['Series Key'] = pd.to_datetime(regional_demand['Series Key'
regional_demand = regional_demand.set_index('Series Key')
regional_demand = regional_demand.astype(float)
regional_demand['demand'] = (regional_demand.iloc[:,0]
                             + regional_demand.iloc[:,1])
regional_demand = regional_demand.drop([
    'EBA.SE-ALL.D.H', 'EBA.TVA-ALL.D.H']
    , axis=1
)
regional_demand.head()
```

executed in 91ms, finished 09:18:13 2021-10-22

Out[5]:

Series Key	demand
2021-10-12 11:00:00+00:00	37467.0
2021-10-12 10:00:00+00:00	35361.0
2021-10-12 09:00:00+00:00	34479.0
2021-10-12 08:00:00+00:00	34484.0
2021-10-12 07:00:00+00:00	35288.0

In [6]:
```
#From NOAA (https://www.ncdc.noaa.gov/cdo-web/confirmation), daily max, min
#and average temperatures from 2016-2021
cols_to_use_clim = ([
    'DATE',
    'DailyMaximumDryBulbTemperature',
    'DailyMinimumDryBulbTemperature',
    'DailyAverageWetBulbTemperature'])
climate = pd.read_csv(
    'files/climate.csv',
    usecols=cols_to_use_clim,
    low_memory=False)
climate = climate.dropna()
climate['DATE'] = pd.to_datetime(climate['DATE'])
climate = climate.set_index('DATE')
climate.head()
```

executed in 365ms, finished 09:18:14 2021-10-22

Out[6]:

DATE	DailyAverageWetBulbTemperature	DailyMaximumDryBulbTemperature	DailyMinimumDryBulbT
2016-01-01 23:59:00	38.0	46.0	
2016-01-02 23:59:00	35.0	47.0	
2016-01-03 23:59:00	36.0	53.0	
2016-01-04 23:59:00	33.0	45.0	
2016-01-05 23:59:00	28.0	44.0	

2.4 Stay Competitive With U.S. Market

In [201]:
```
#From EIA.gov, measured monthly, in million kwh
us_solar = pd.read_csv('files/solar_generation.csv')[6:]
us_solar = (us_solar[us_solar['Description'] ==
    'Distributed Solar Photovoltaic Generation: Residential Sector'])
us_solar = us_solar[us_solar['Value'] != 'Not Available']
us_solar['Value'] = us_solar['Value'].astype(float)
us_solar['YYYYMM'] = us_solar['YYYYMM'].astype(str)
us_solar = us_solar[~us_solar['YYYYMM'].str.endswith('13')]
us_solar['YYYYMM'] = pd.to_datetime((us_solar['YYYYMM']), format='%Y%m')
us_solar = us_solar.set_index('YYYYMM')
us_solar = us_solar[['Value']]
us_solar.index.freq = 'MS'
us_solar.head()
```

executed in 25ms, finished 10:22:13 2021-10-22

Out[201]:

YYYYMM	Value
1989-01-01	0.560
1989-02-01	0.604
1989-03-01	0.832
1989-04-01	0.917
1989-05-01	1.012

In [8]:
```
#From EIA.gov, measured monthly, in kwh
ga_solar = pd.read_csv('files/ga_solar_production.csv')[6:]
ga_solar['Series Key'] = pd.to_datetime(ga_solar['Series Key'], format='%Y%
ga_solar = ga_solar.set_index('Series Key')
ga_solar.columns = ['value']
ga_solar['value'] = ga_solar['value'] .astype(float)
ga_solar = ga_solar.sort_index()
ga_solar.index.freq = 'MS'
ga_solar = ga_solar.sort_index()
ga_solar.head()
```

executed in 11ms, finished 09:18:14 2021-10-22

Out[8]:

Series Key	value
2014-01-01	6.62759
2014-02-01	6.81839
2014-03-01	8.70972
2014-04-01	9.37660
2014-05-01	10.17159

In [9]:
```
#From EIA.gov, measured monthly, in millon kwh
net_metering_2020 = pd.read_excel(
    'files/net_metering2020.xlsx',
    sheet_name = 'Monthly_Totals-States' ,
    header=3)
net_metering_2020 = (net_metering_2020.loc
                     [:,
                      ['State','Residential',
                       'Residential.14',
                       'Residential.15']])
for col in net_metering_2020.columns[1:]:
    net_metering_2020[col] = pd.to_numeric(net_metering_2020[col],
                                           errors = 'coerce')

net_metering_2020 = net_metering_2020.groupby('State').sum()
net_metering_2020.reset_index(inplace=True)
net_metering_2020.columns = ([
    'state',
    'residential_solar_capacity',
    'residential_solar_customers',
    'energy_sold'
])

net_metering_2020.head()
```

executed in 4.38s, finished 09:18:18 2021-10-22

Out[9]:

	state	residential_solar_capacity	residential_solar_customers	energy_sold
0	AK	61.670	14562.0	781.821
1	AL	0.000	0.0	0.000
2	AR	278.620	26094.0	1903.982
3	AZ	13437.813	2031545.0	220581.902
4	CA	75485.035	13533399.0	123960.829

3 Initial Exploration

3.1 Reduce Dependence on Imported Electricity

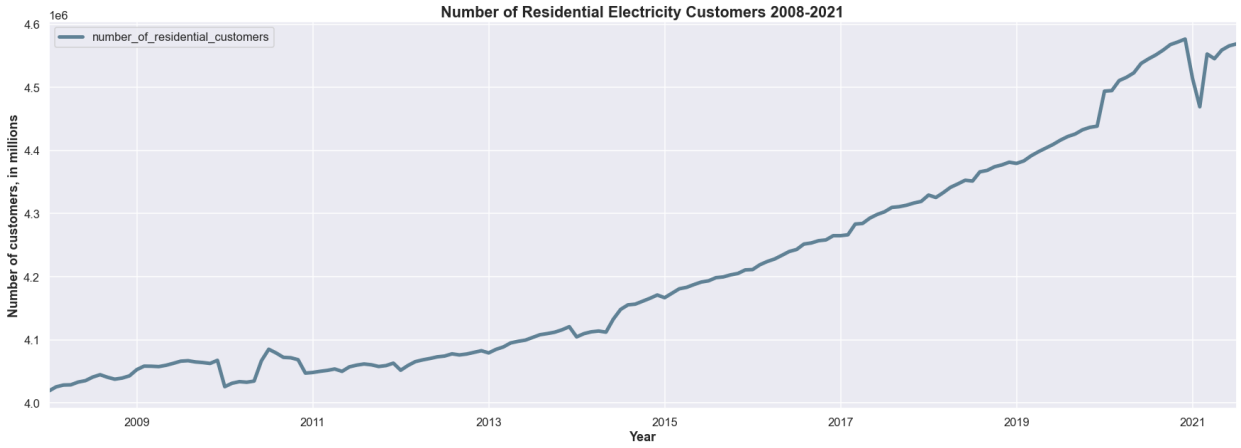
In [10]:
```
#Examine the customer data. There are 163 non-null observations.
customers.info()
```

executed in 7ms, finished 09:18:18 2021-10-22

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 163 entries, 2008-01-01 to 2021-07-01
Freq: MS
Data columns (total 1 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   number_of_residential_customers  163 non-null    int64
dtypes: int64(1)
memory usage: 2.5 KB
```

In [11]:
```
#Plot the number of customers
customers.plot(
    color=NEUTRAL,
    figsize=(30,10),
    linewidth=5
)
plt.title(
    'Number of Residential Electricity Customers 2008-2021',
    fontsize='large',
    weight='bold'
)
plt.ylabel(
    'Number of customers, in millions',
    weight='bold'
)
plt.xlabel(
    'Year',
    weight='bold'
);
```

executed in 274ms, finished 09:18:18 2021-10-22

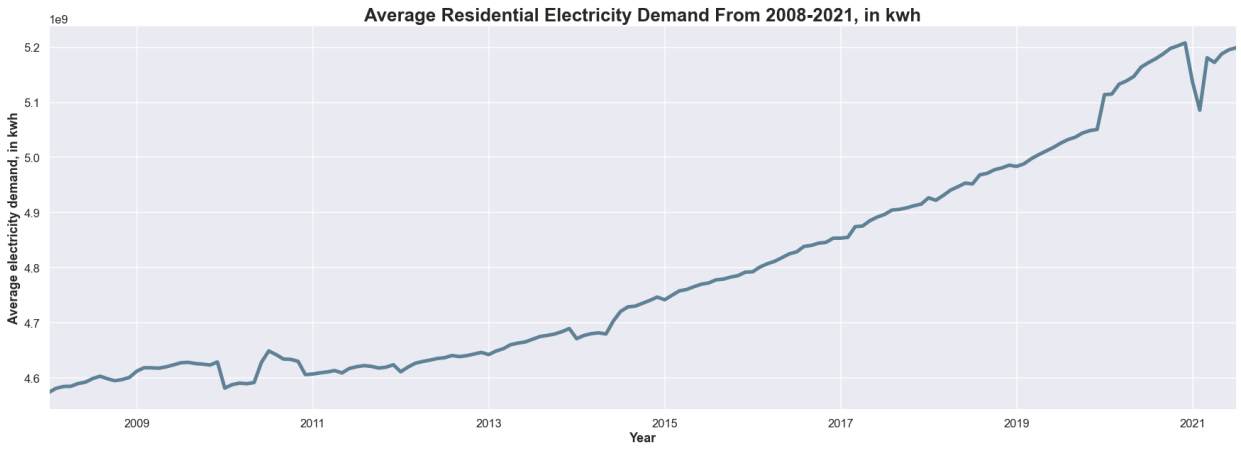


From 2008 to 2013, the number of residential customers stayed relatively constant at just over 4 million. The number of customers has been steadily increasing since then, with a brief sharp increase in 2020, most likely due to the pandemic.

The monthly (or more frequent) residential energy demand for Georgia is not available. I will instead use the number of customers and the average electricity usage per household to estimate the energy demand per month.

In [12]:
```
# Average residential kwh/month from chooseenergy.com
avg_kwh = 1138
customers['total_kwh'] = customers['number_of_residential_customers'] * avg
customers['total_kwh'].plot(
    color=NEUTRAL,
    figsize=(30,10),
    linewidth=5)
plt.title(
    'Average Residential Electricity Demand From 2008-2021, in kwh',
    fontsize='x-large',
    weight='bold'
)
plt.ylabel(
    'Average electricity demand, in kwh',
    weight='bold'
)
plt.xlabel(
    'Year',
    weight='bold'
);
```

executed in 218ms, finished 09:18:19 2021-10-22



In [13]:
```
#Select only the kwh column
energy_demand = customers.copy()['total_kwh']
```

executed in 3ms, finished 09:18:19 2021-10-22

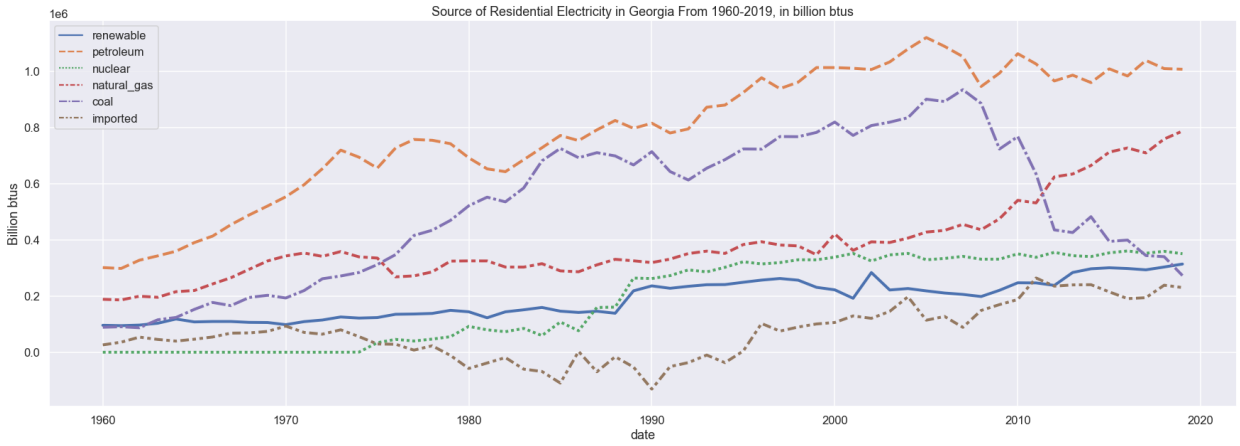
In [14]:
```
#Examine the electricity source data. There are 60 non-null observations.
by_source.info()
```

executed in 7ms, finished 09:18:19 2021-10-22

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 60 entries, 2019-01-01 to 1960-01-01
Data columns (total 8 columns):
 #   Column            Non-Null Count  Dtype  
---  ------            --------------  -----  
 0   renewable         60 non-null     float64
 1   petroleum         60 non-null     float64
 2   nuclear           60 non-null     float64
 3   natural_gas       60 non-null     float64
 4   coal              60 non-null     float64
 5   total             60 non-null     float64
 6   imported          60 non-null     float64
 7   percent_imported  60 non-null     float64
dtypes: float64(8)
memory usage: 4.2 KB
```

In [15]:
```
#Select only the columns to plot
by_source_only = by_source.drop(['total', 'percent_imported'], axis=1)

fig,ax = plt.subplots(figsize=(30,10))
sns.lineplot(
    data=by_source_only,
    palette=PALETTE,
    linewidth=4)
plt.title('Source of Residential Electricity in Georgia From 1960-2019, in
plt.ylabel('Billion btus');
```

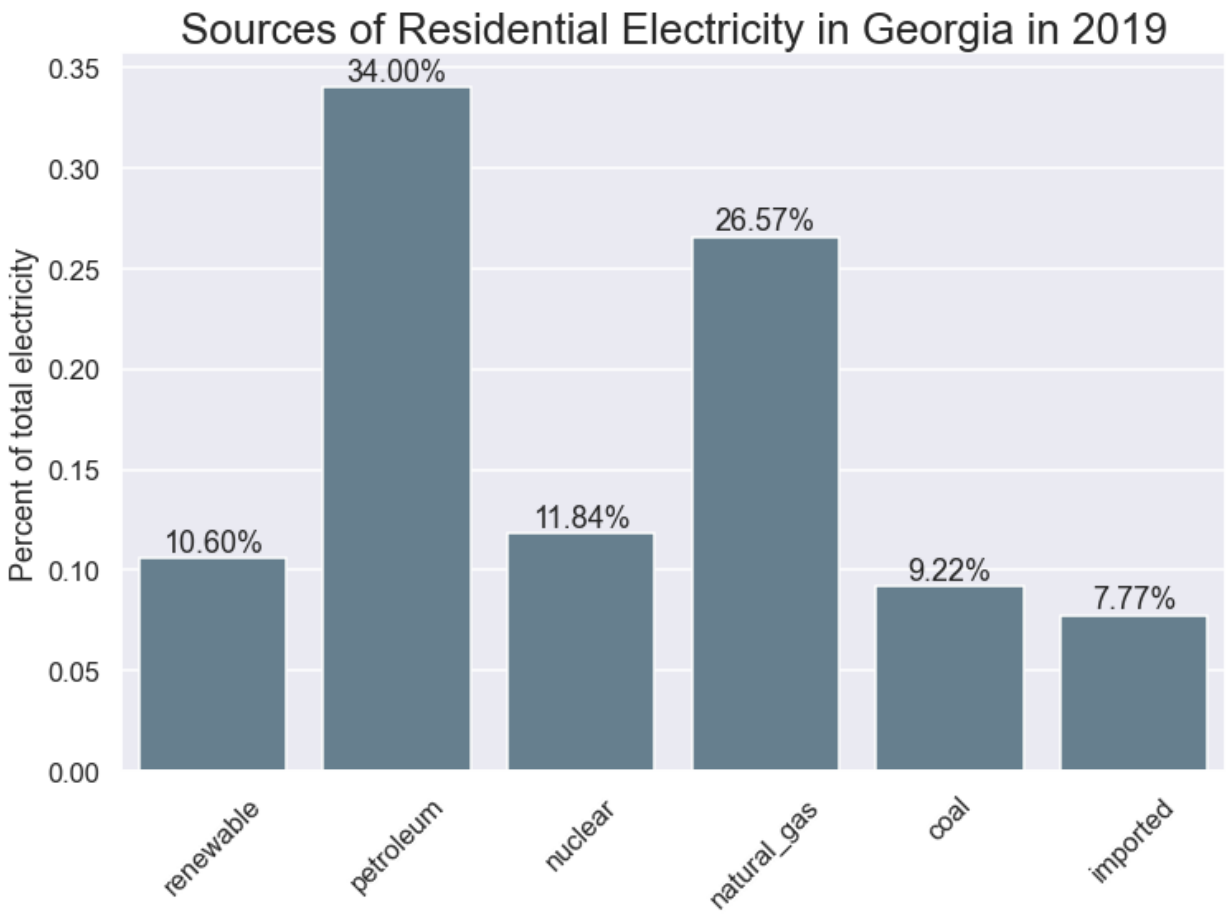
executed in 322ms, finished 09:18:19 2021-10-22



Natural gas use is increasing rapidly while the use of coal to generate electricity is decreasing. Renewables, nuclear and petroleum have remained relatively steady over the past 15 years

In [16]:
```
#Plot percent of each source of residential electricity
fig,ax = plt.subplots(figsize=(12,8))
g = sns.barplot(
    x=by_source_only.columns,
    y=by_source_only.iloc[0]/by_source.loc['2019','total'][0],
    color=NEUTRAL
)
for p in g.patches:
    g.annotate(format(f'{p.get_height()*100:.2f}%'),
                   (p.get_x() + p.get_width() / 2., p.get_height()),
                   ha = 'center', va = 'center',
                   xytext = (0, 9),
                   textcoords = 'offset points')
plt.title(
    'Sources of Residential Electricity in Georgia in 2019',
    fontsize='x-large')
plt.xticks(rotation=45)
plt.ylabel('Percent of total electricity');
```

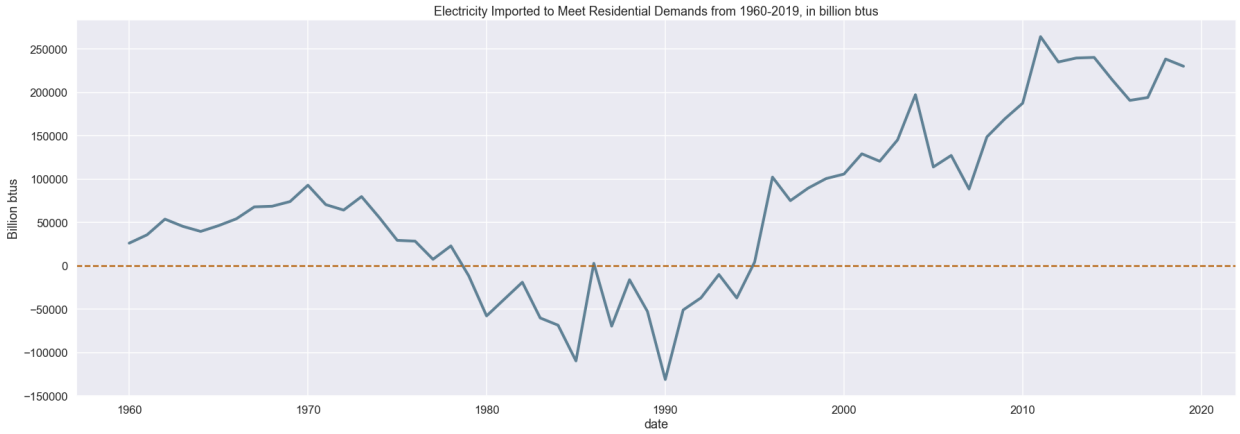
executed in 164ms, finished 09:18:19 2021-10-22



According to the most recent data in 2019, petroleum and natural gas account for over 50% of the electricity. According to the EIA, Georgia does not have any natural gas, oil or coal resources, so all of those raw materials have to be imported from other areas. 8% of the electricity is directly imported from other states.

In [17]:
```
#Plot electricity imported
fig,ax = plt.subplots(figsize=(30,10))
sns.lineplot(
    data=by_source['imported'],
    color=NEUTRAL,
    linewidth=4)
plt.axhline(0,
            linestyle='--',
            color=BRICK)
plt.title(
    'Electricity Imported to Meet Residential Demands from 1960-2019, in bi
)
plt.ylabel('Billion btus');
```

executed in 241ms, finished 09:18:19 2021-10-22



In the 1980s, Georgia was producing more electricity than it used and was able to export the excess. Since the mid-1990s, the amount of electricity imported has overall been increasing.

3.2 Mitigate Impact of Rising Natural Gas Prices

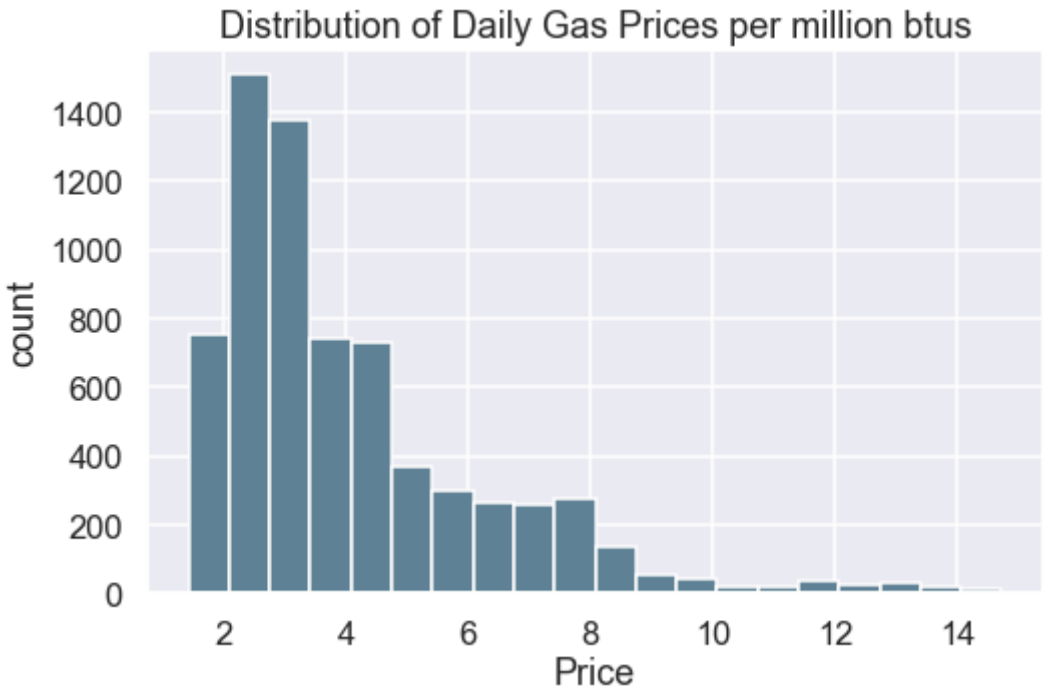
In [18]:
```
#Examine the gas price data. There are 6968 non-null observations.
gas_price.info()
```

executed in 6ms, finished 09:18:19 2021-10-22

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 6968 entries, 2021-10-05 to 1994-01-19
Data columns (total 1 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   avg_price  6968 non-null   float64
dtypes: float64(1)
memory usage: 108.9 KB
```

In [19]:
```
# Gas prices are clustered around $3.00/ million btu units with a long
# right tail
gas_price.hist(
    bins=20,
    color=NEUTRAL,
    figsize=(8,5))
plt.title('Distribution of Daily Gas Prices per million btus')
plt.xlabel('Price')
plt.ylabel('count');
```

executed in 154ms, finished 09:18:19 2021-10-22



In [20]:
```
gas_price.describe()
```

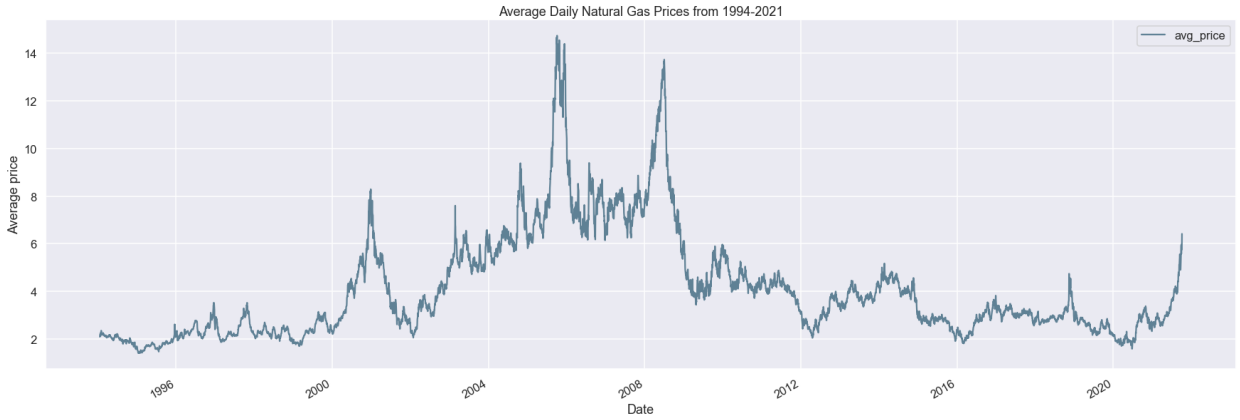
executed in 10ms, finished 09:18:19 2021-10-22

Out[20]:

	avg_price
count	6968.000000
mean	4.082263
std	2.244756
min	1.414750
25%	2.502000
50%	3.280750
75%	4.969750
max	14.737750

In [21]:
```
#Examine gas prices over time
gas_price.plot(
    figsize=(30,10),
    color=NEUTRAL)
plt.title('Average Daily Natural Gas Prices from 1994-2021')
plt.ylabel('Average price')
plt.xlabel('Date');
```

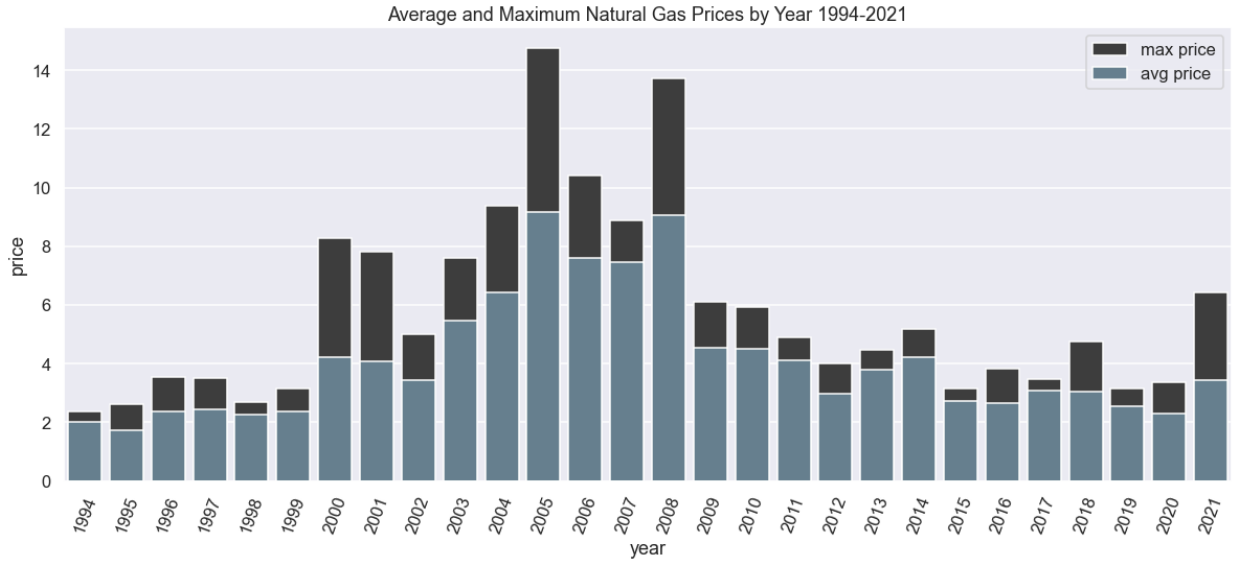
executed in 238ms, finished 09:18:20 2021-10-22



Gas prices were relatively steady from 1994-2000 and again from 2012-2020. They increased between 2000 and 2012, with two sharp spikes around the max price of $14.74. In 2021, prices appear to be sharply increasing again.

In [22]:
```
#Plot average and maximin price of gas per year
avg_gas_by_year = gas_price.resample('A').mean()
max_gas_by_year = gas_price.resample('A').max()
avg_gas_by_year['year'] = avg_gas_by_year.index.year
max_gas_by_year['year'] = max_gas_by_year.index.year
fig,ax = plt.subplots(figsize=(20,8))
sns.barplot(
    data=max_gas_by_year,
    x='year',
    y='avg_price',
    color=DARK_NEUTRAL,
    label='max price')
sns.barplot(
    data=avg_gas_by_year,
    x='year',
    y='avg_price',
    color=NEUTRAL,
    label='avg price')
ax.legend()
plt.xticks(rotation=70)
plt.ylabel('price')
plt.title('Average and Maximum Natural Gas Prices by Year 1994-2021');
```

executed in 441ms, finished 09:18:20 2021-10-22



3.3 Decrease Strain on Power Grid During High Demand Periods

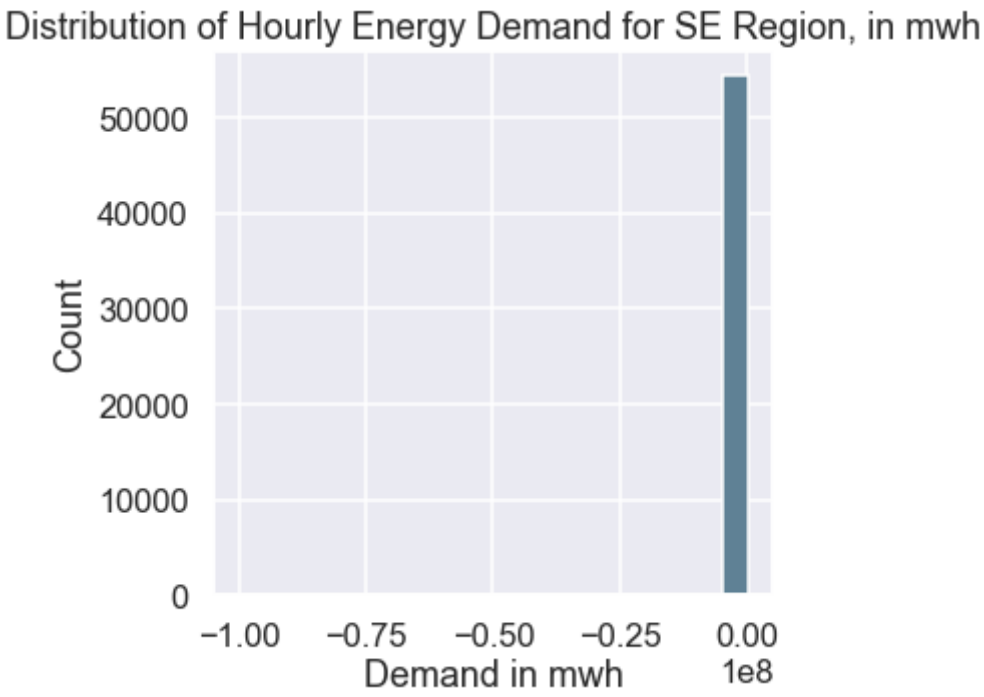
In [23]:
```
#Summarize the data
regional_demand.describe(), regional_demand.isna().sum()
```

executed in 12ms, finished 09:18:20 2021-10-22

Out[23]:
```
(              demand
 count  5.427300e+04
 mean   4.275804e+04
 std    4.311303e+05
 min   -9.987333e+07
 25%    3.879700e+04
 50%    4.304600e+04
 75%    5.016700e+04
 max    8.429300e+04,
 demand    813
 dtype: int64)
```

In [24]:
```
#Plot energy demand
regional_demand.hist(figsize=(5,5), color=NEUTRAL, bins=20)
plt.title('Distribution of Hourly Energy Demand for SE Region, in mwh')
plt.xlabel('Demand in mwh')
plt.ylabel('Count');
```

executed in 143ms, finished 09:18:20 2021-10-22



There are obviously some extreme outliers, most likely due to data entry or equipment errors because negative values do not have meaning within this context. Additionally, there are 813 null entries that will need to be addressed.

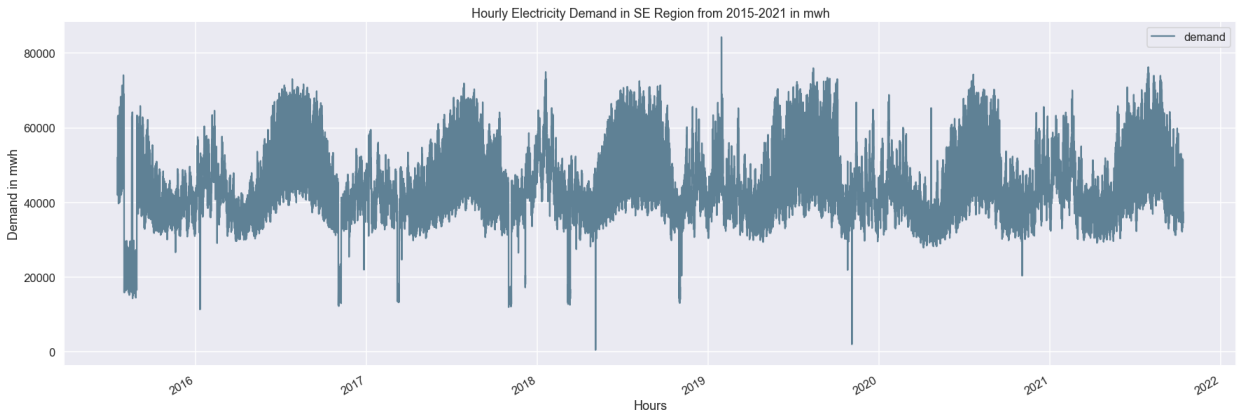
In [25]:
```
#Examine missing values
regional_demand[regional_demand['demand'].isna()][:40]
```

executed in 9ms, finished 09:18:20 2021-10-22

2019-10-01 23:00:00+00:00	NaN
2019-10-01 22:00:00+00:00	NaN
2019-10-01 21:00:00+00:00	NaN
2019-10-01 20:00:00+00:00	NaN
2019-10-01 19:00:00+00:00	NaN
2019-10-01 18:00:00+00:00	NaN
2019-10-01 17:00:00+00:00	NaN
2019-10-01 16:00:00+00:00	NaN
2019-10-01 15:00:00+00:00	NaN
2019-10-01 14:00:00+00:00	NaN

In [26]:
```
#Plot the data above 0
regional_demand[regional_demand['demand']>0].plot(
    figsize=(30,10),
    color=NEUTRAL)
plt.xlabel('Hours')
plt.ylabel('Demand in mwh')
plt.title('Hourly Electricity Demand in SE Region from 2015-2021 in mwh');
```

executed in 341ms, finished 09:18:21 2021-10-22



In [27]:
```
#Fine the first quantile to get a sense of what qualifies as an outlier
regional_demand[regional_demand['demand']>0].quantile(.1)
```

executed in 6ms, finished 09:18:21 2021-10-22

Out[27]:
```
demand    34728.0
Name: 0.1, dtype: float64
```

In [28]:
```
#Calculate the percent of values below 25,000 mwh
regional_demand[(
    regional_demand['demand'] < 25000)].shape[0]/regional_demand.shape[0]
```

executed in 4ms, finished 09:18:21 2021-10-22

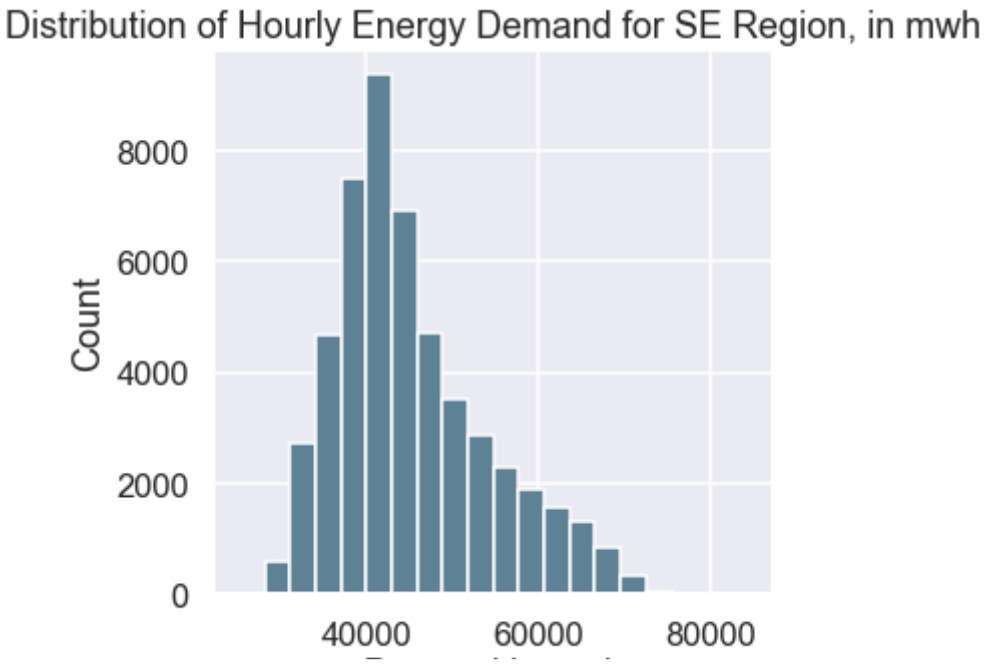
Out[28]:
```
0.01824419997821588
```

The missing values occur over consecutive hours, perhaps when equipment was malfunctioning. Because the data will be resampled at the daily level with the maximum demand for each day, these rows can simply be dropped.

There is suspect data below the value of 30,000 kwh. Although these may be associated with power outages in the region, I was unable to substantiate that. That also would not explain the artifact in 2015, where data is clustered at 20,000. I am going to start the time series after the anomaly in 2015 and limit it to values above 25,000 kwh, as the first quantile of the data is at 34,728. This eliminates 1.8% of the data points.

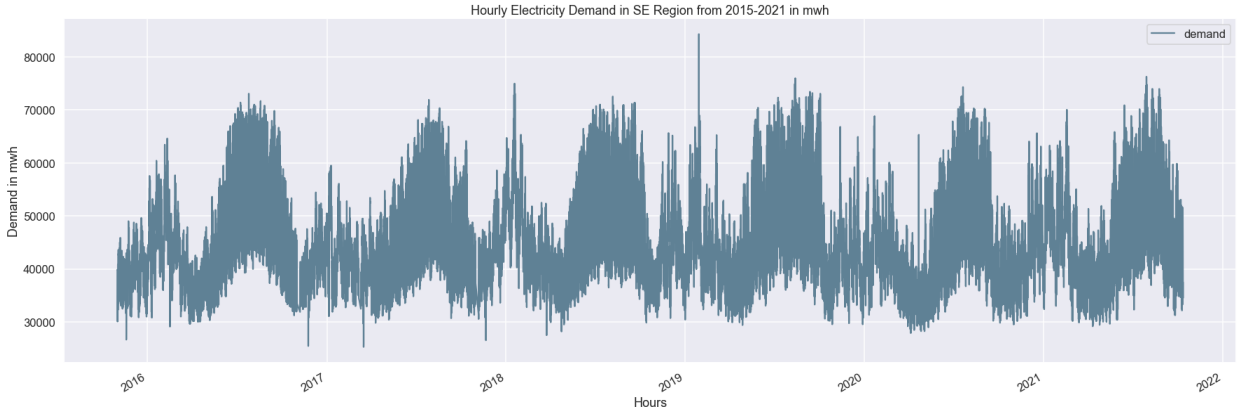
In [29]:
```
#Remove null values and outliers
regional_demand = regional_demand[regional_demand['demand'] > 25000].dropna
regional_demand = regional_demand[regional_demand.index >= '2015-11']

#Plot energy demand after removing outliers and null values
regional_demand.hist(figsize=(5,5), color=NEUTRAL, bins=20)
plt.title('Distribution of Hourly Energy Demand for SE Region, in mwh')
plt.xlabel('Demand in mwh')
plt.ylabel('Count');
```

executed in 267ms, finished 09:18:21 2021-10-22



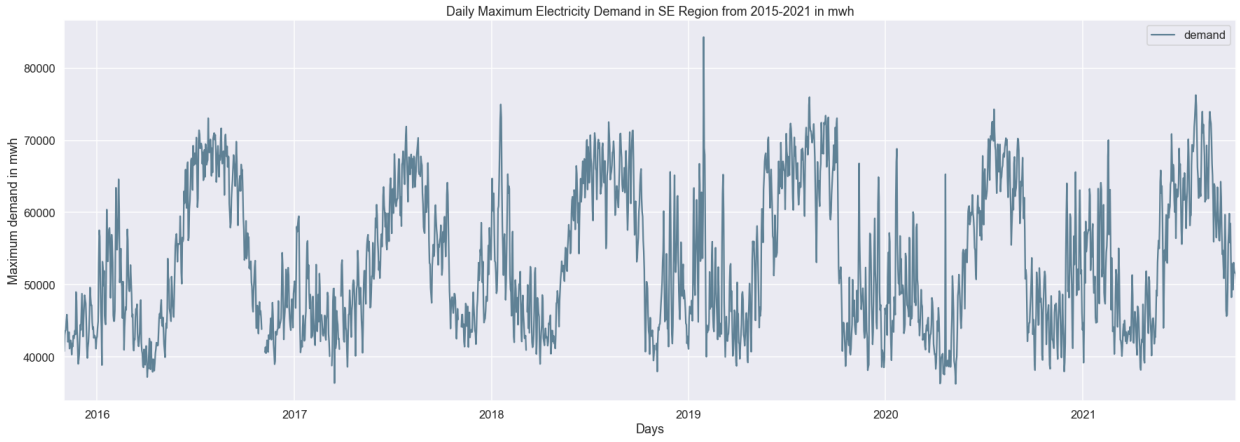
In [30]:
```
#Plot energy demand after removing outliers and null values
regional_demand.plot(
    figsize=(30,10),
    color=NEUTRAL)
plt.xlabel('Hours')
plt.ylabel('Demand in mwh')
plt.title('Hourly Electricity Demand in SE Region from 2015-2021 in mwh');
```

executed in 361ms, finished 09:18:21 2021-10-22



In [31]:
```
#Resample the data at a daily level. Find the maximum demand, since we are
#looking at the strain on the power grid.
daily_demand = regional_demand.resample('D').max()
daily_demand.plot(
    figsize=(30,10),
    color=NEUTRAL)
plt.xlabel('Days')
plt.ylabel('Maximum demand in mwh')
plt.title(
    'Daily Maximum Electricity Demand in SE Region from 2015-2021 in mwh'
);
```

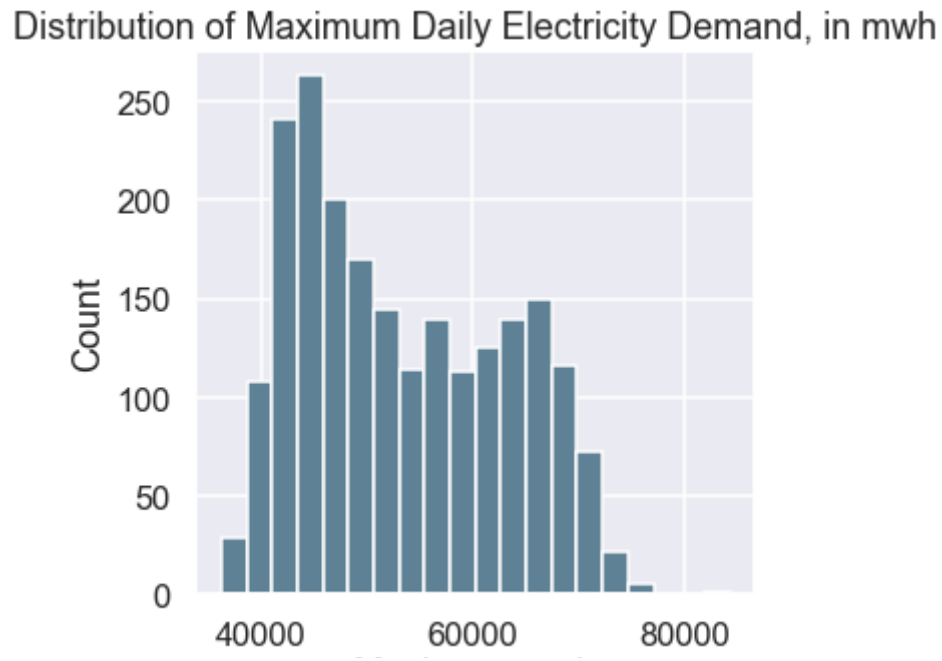
executed in 294ms, finished 09:18:22 2021-10-22



The daily maximum demand on the residential electrical grid shows a clear seasonal pattern, with demand at its highest in the summer months and a secondary peak in the winter. This makes sense, as HVAC is a major use of residential electricity.

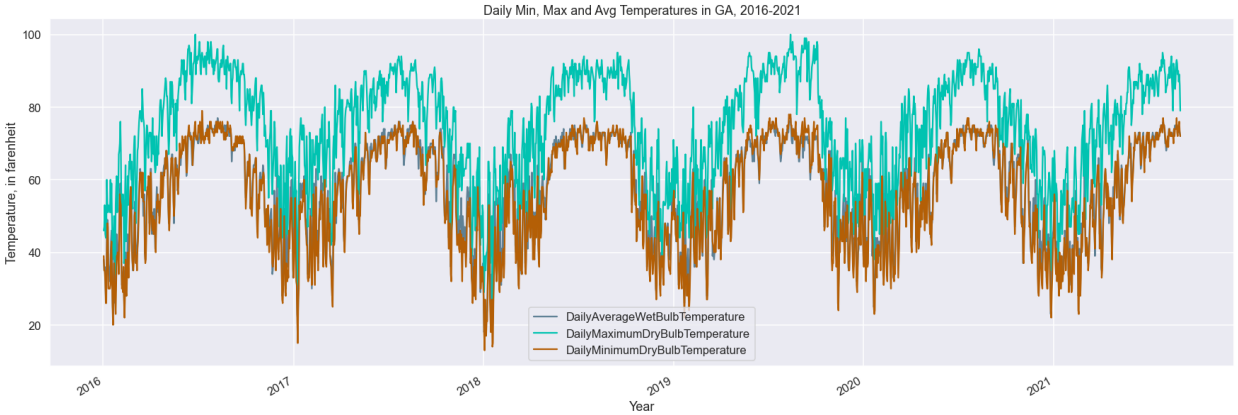
In [32]:
```
#Plot the distribution of the demand
daily_demand.hist(bins=20, color=NEUTRAL, figsize=(5,5))
plt.title('Distribution of Maximum Daily Electricity Demand, in mwh')
plt.xlabel('Maximum mwh')
plt.ylabel('Count');
```

executed in 132ms, finished 09:18:22 2021-10-22



In [33]:
```
#Plot the daily temperature data
climate.plot(figsize=(30,10), color = [NEUTRAL, HIGHLIGHT,BRICK])
plt.title('Daily Min, Max and Avg Temperatures in GA, 2016-2021')
plt.xlabel('Year')
plt.ylabel('Temperature, in farenheit');
```

executed in 290ms, finished 09:18:22 2021-10-22



In [34]:
```
#Create a dataframe with temperature and demand data from 2016-2021
energy= daily_demand.copy()
energy = energy['2016':]
energy.index = pd.to_datetime(energy.index, format = '%Y%m%d').date

climate.index = pd.to_datetime(climate.index,format = '%Y%m%d').date
demand_temp = pd.concat([energy, climate], axis=1).dropna()
demand_temp.columns=['demand', 'avg_temp','max_temp','min_temp']
```

executed in 12ms, finished 09:18:22 2021-10-22

In [35]:
```
#Find the overall average temperature and create columns to show the max an
#min deviation from average
overall_mean = demand_temp['avg_temp'].mean()
demand_temp['above_avg'] = demand_temp['max_temp'] - overall_mean
demand_temp['below_avg'] = demand_temp['min_temp'] - overall_mean
demand_temp.head()
```

executed in 10ms, finished 09:18:22 2021-10-22

Out[35]:

	demand	avg_temp	max_temp	min_temp	above_avg	below_avg
2016-01-01	42823.0	38.0	46.0	39.0	-11.805474	-18.805474
2016-01-02	44050.0	35.0	47.0	35.0	-10.805474	-22.805474
2016-01-03	44933.0	36.0	53.0	35.0	-4.805474	-22.805474
2016-01-04	52829.0	33.0	45.0	32.0	-12.805474	-25.805474
2016-01-05	57543.0	28.0	44.0	26.0	-13.805474	-31.805474

In [36]:
```
def get_extreme(above, below):
    """Takes in the deviation from average and retuns the most extreme valu
    if above > 0 and below > 0:
        return max(above,below)
    return min(above,below)
```

executed in 3ms, finished 09:18:22 2021-10-22

In [37]:
```
#Create a column for the largest deivation from average in a day
demand_temp['extreme'] = demand_temp.apply(
    lambda x:
    get_extreme(x['above_avg'],
                x['below_avg']),
    axis=1)
demand_temp.head()
```

executed in 28ms, finished 09:18:22 2021-10-22

Out[37]:

	demand	avg_temp	max_temp	min_temp	above_avg	below_avg	extreme
2016-01-01	42823.0	38.0	46.0	39.0	-11.805474	-18.805474	-18.805474
2016-01-02	44050.0	35.0	47.0	35.0	-10.805474	-22.805474	-22.805474
2016-01-03	44933.0	36.0	53.0	35.0	-4.805474	-22.805474	-22.805474
2016-01-04	52829.0	33.0	45.0	32.0	-12.805474	-25.805474	-25.805474
2016-01-05	57543.0	28.0	44.0	26.0	-13.805474	-31.805474	-31.805474

In [38]:
```
#Examine the correlations between the features
demand_temp.corr()
```

executed in 10ms, finished 09:18:22 2021-10-22

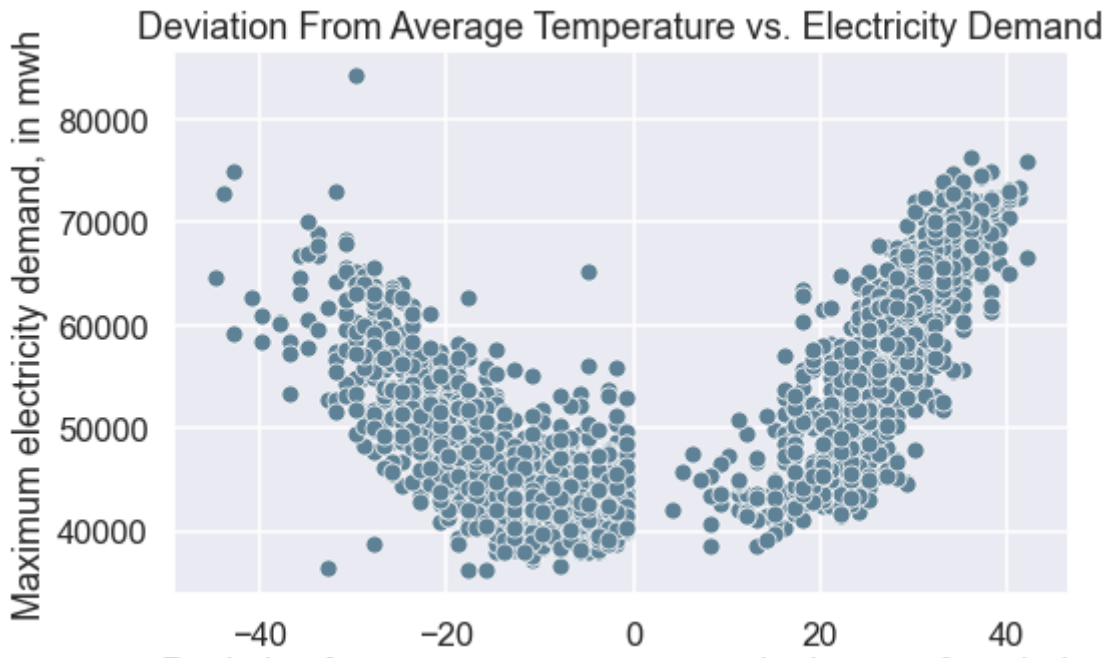
Out[38]:

	demand	avg_temp	max_temp	min_temp	above_avg	below_avg	extreme
demand	1.000000	0.482744	0.504633	0.509601	0.504633	0.509601	0.581964
avg_temp	0.482744	1.000000	0.932538	0.982337	0.932538	0.982337	0.952741
max_temp	0.504633	0.932538	1.000000	0.923070	1.000000	0.923070	0.924941
min_temp	0.509601	0.982337	0.923070	1.000000	0.923070	1.000000	0.972330
above_avg	0.504633	0.932538	1.000000	0.923070	1.000000	0.923070	0.924941
below_avg	0.509601	0.982337	0.923070	1.000000	0.923070	1.000000	0.972330
extreme	0.581964	0.952741	0.924941	0.972330	0.924941	0.972330	1.000000

The extreme column shows the greatest correlation with electricity demand (0.58). In other words, the further away from "normal" the daily max or min temperature is, the greater the demand on the grid.

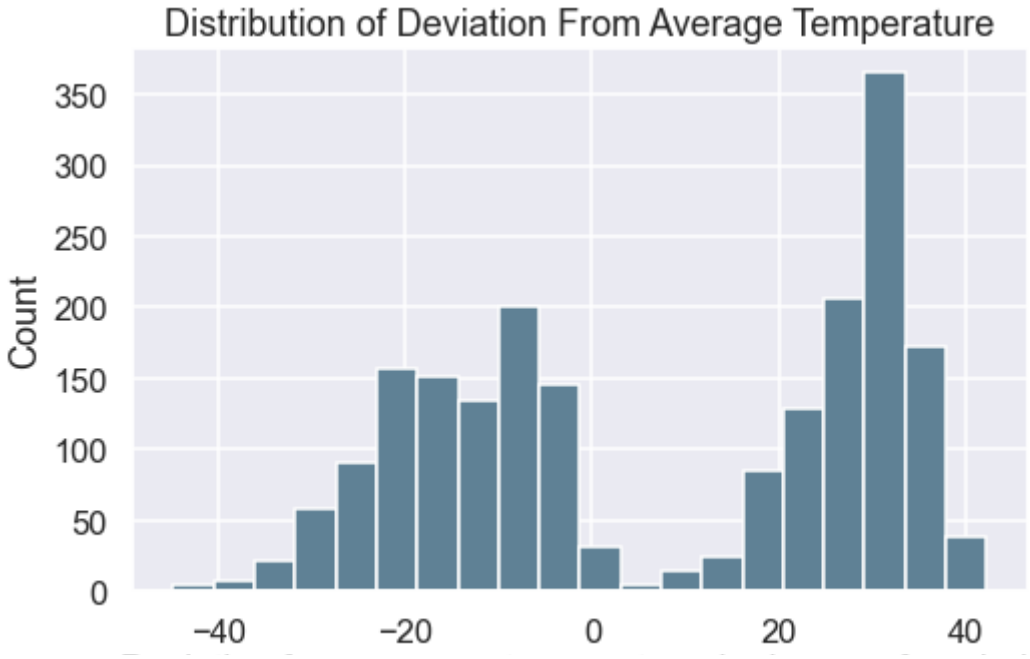
In [39]:
```
#Plot extreme vs. demand
fig,ax = plt.subplots(figsize=(8, 5))
sns.scatterplot(
    data = demand_temp,
    x = 'extreme',
    y='demand',
    color=NEUTRAL)
plt.title('Deviation From Average Temperature vs. Electricity Demand')
plt.xlabel('Deviation from average temperature, in degrees farenheit')
plt.ylabel('Maximum electricity demand, in mwh');
```

executed in 146ms, finished 09:18:22 2021-10-22



In [40]:
```
#Plot the distribution of extreme
demand_temp['extreme'].hist(
    figsize=(8,5),
    bins=20,
    color=NEUTRAL
)
plt.title('Distribution of Deviation From Average Temperature')
plt.xlabel('Deviation from average temperature, in degrees farenheit')
plt.ylabel('Count');
```

executed in 145ms, finished 09:18:22 2021-10-22



There is definitely a correlation between temperature extremes and demand, with the relationship appearing stronger and more linear with the above-average temperatures than below.

It is clear there are two distinct populations, one for hot days and one for cold. I will split the data in two and perform regression on each one separately.

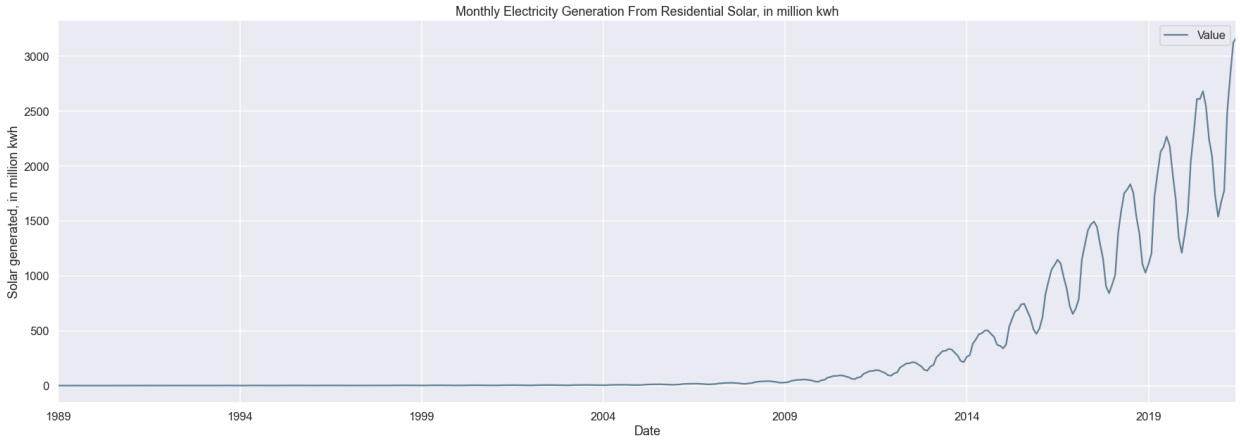
In [41]:
```
#Create two different dataframes, one for hot days and one for cold.
demand_above = demand_temp[demand_temp['extreme']>0]
demand_below = demand_temp[demand_temp['extreme']<0]
```

executed in 4ms, finished 09:18:22 2021-10-22

3.4 Stay Competitive With U.S. Market

In [202]:
```
#Plot the solar data
us_solar.plot(figsize=(30,10), color=NEUTRAL)
plt.title('Monthly Electricity Generation From Residential Solar, in millio
plt.xlabel('Date')
plt.ylabel('Solar generated, in million kwh');
```

executed in 321ms, finished 10:22:18 2021-10-22



4 Data Preparation

For the time series data, the first goal is to check for stationarity and transform the data to make it more stationary by removing trend and/or seasonality.

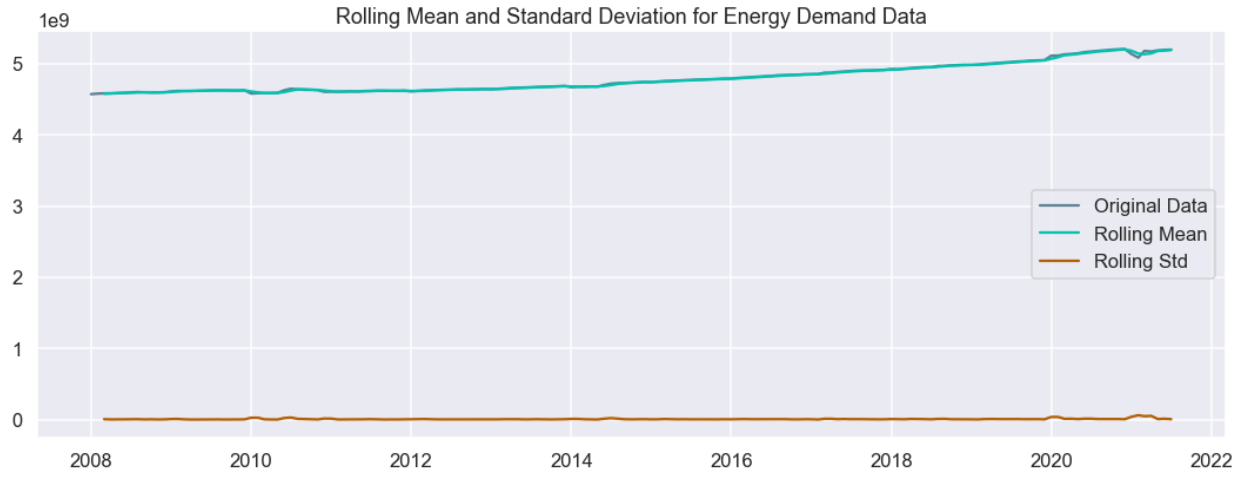
In [43]:
```
def plot_rolling(df, periods, name):
    """Takes in a data frame, the number of periods to use in a window and
    name of the data and returns a plot of the orginial data with its rolli
    mean and standard deviation."""

    fig, ax = plt.subplots(figsize=(15,6))
    ax.plot(
        df,
        label='Original Data',
        color=NEUTRAL
    )
    ax.plot(
        df.rolling(periods).mean(),
        label='Rolling Mean',
        color=HIGHLIGHT
    )
    ax.plot(
        df.rolling(periods).std(),
        label='Rolling Std',
        color=BRICK
    )
    ax.legend()
    plt.title(f'Rolling Mean and Standard Deviation for {name} Data')
    fig.tight_layout()

    return fig,ax
```

executed in 4ms, finished 09:18:23 2021-10-22

4.1 Reduce Dependence on Imported Electricity

In [44]:
```
#Check the rolling mean and standard deviation of energy demand
plot_rolling(energy_demand, 3, 'Energy Demand');
```

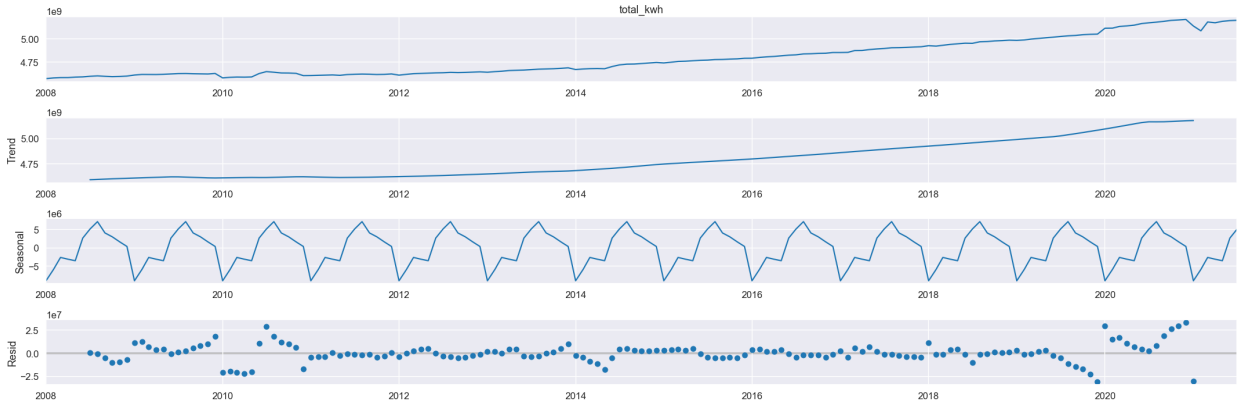
executed in 241ms, finished 09:18:23 2021-10-22



The standard deviation is relativity consistent, which shows that there is little seasonality. However, the mean is not constant over time, showing a clear positive trend.

In [45]:
```
#Examine components of customer data
plt.rcParams['figure.figsize'] = 30,10
decompose = seasonal_decompose(energy_demand).plot()
```

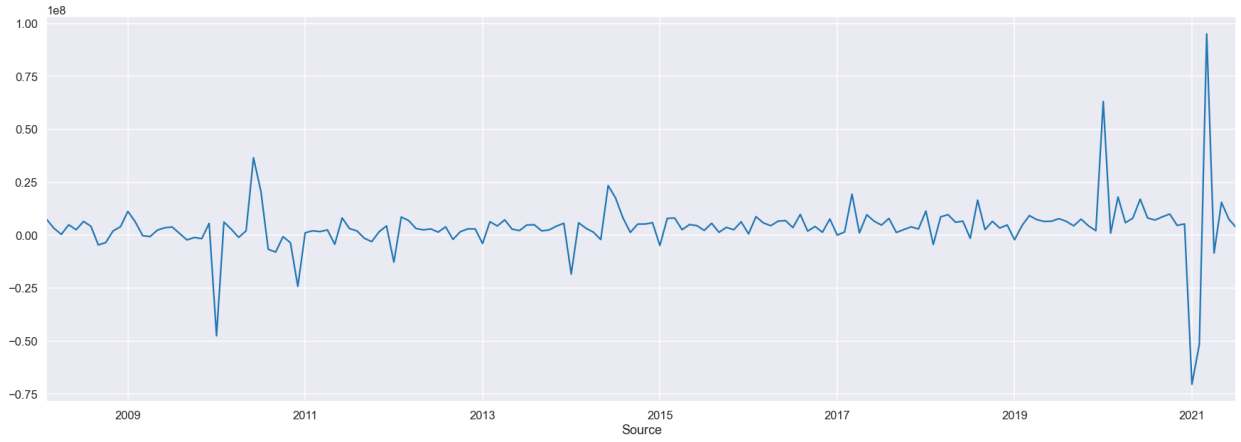
executed in 674ms, finished 09:18:24 2021-10-22



The decomposition plot shows a seasonal pattern, but a strong seasonal variation would not be expected in the number of monthly customers. It appears that most of this data is trend, showing that it is increasing as a function of time.

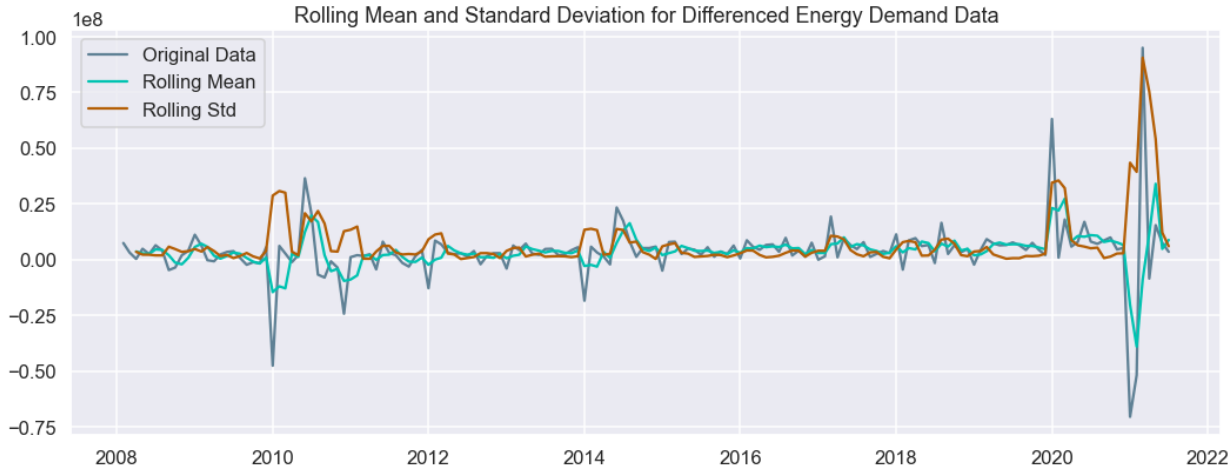
In [46]:
```
#Plot the first difference
demand_diff = energy_demand.diff().dropna().plot(figsize=(30,10))
```

executed in 195ms, finished 09:18:24 2021-10-22



In [47]:
```
#Check the rolling mean and standard deviation of differenced energy demand
plot_rolling(energy_demand.diff().dropna(), 3, 'Differenced Energy Demand')
```

executed in 243ms, finished 09:18:24 2021-10-22



Taking the first difference removes the trend and shows that there is some variability that is not explained by the linear trend. The Dickey Fuller test confirms that taking the first difference makes the data more stationary (p-value of 0.14 vs 0.99), although it is still not stationary.

In [199]:
```
print(
    f'p-value original data: {adfuller(energy_demand)[1]}')
print(
    f'p-value differenced data: {adfuller(energy_demand.diff().dropna())[1]
print(
    f'p-value logged and differenced data:\
    {adfuller(np.log(energy_demand).diff().dropna())[1]}')
print(
    f'p-value root and differenced data:\
    {adfuller(np.sqrt(energy_demand).diff().dropna())[1]}')
```

executed in 29ms, finished 10:21:31 2021-10-22

```
p-value original data: 0.9989690341772517
p-value differenced data: 0.142265483739356
p-value logged and differenced data:    0.13297539330146563
p-value root and differenced data:    0.13754444446141528
```

Logged data will be used because that improved the stationarity.

In [49]:
```
#Split the data so that there are 12 years in the training set and just und
#two years in the test set.

demand_split = '2019-12-01'
log_demand = np.log(energy_demand)
demand_train = log_demand[:demand_split]
demand_test = log_demand[demand_split:]

demand_train.index = pd.DatetimeIndex(demand_train.index.values,
                                      freq=demand_train.index.inferred_freq)

demand_train.shape, demand_test.shape
```

executed in 6ms, finished 09:18:24 2021-10-22

Out[49]:
```
((144,), (20,))
```

This split means that the model is not trained on data during the pandemic. This means that it won't be effective at predicting the temporary volatility in residential energy demand caused by Covid, but that it will be better at picking up the overall longer term trends.

4.2 Mitigate Impact of Rising Natural Gas Prices

In [50]:
```
#Because I am more concerned with longer-term trends than daily fluctuation
#the data will be resampled by weekly average price. This leaves 1447
#observations.
gas_weekly = gas_price.resample('W').mean()
gas_weekly.describe()
```

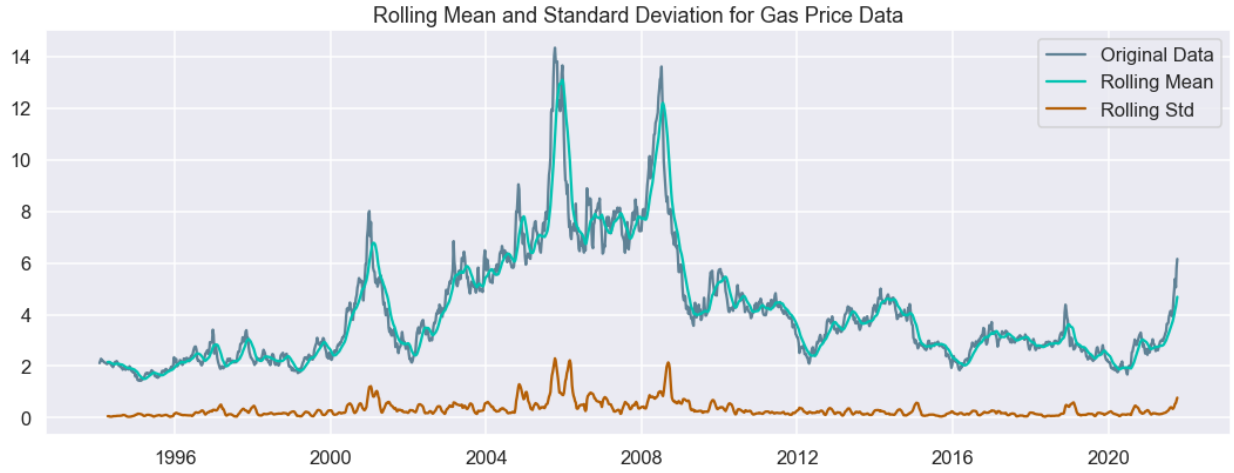
executed in 23ms, finished 09:18:24 2021-10-22

Out[50]:

	avg_price
count	1447.000000
mean	4.085318
std	2.241451
min	1.435050
25%	2.495550
50%	3.285100
75%	4.990100
max	14.338250

In [51]:
```
#Check the rolling mean and standard deviation of gas_prices
plot_rolling(gas_weekly, 12, 'Gas Price');
```

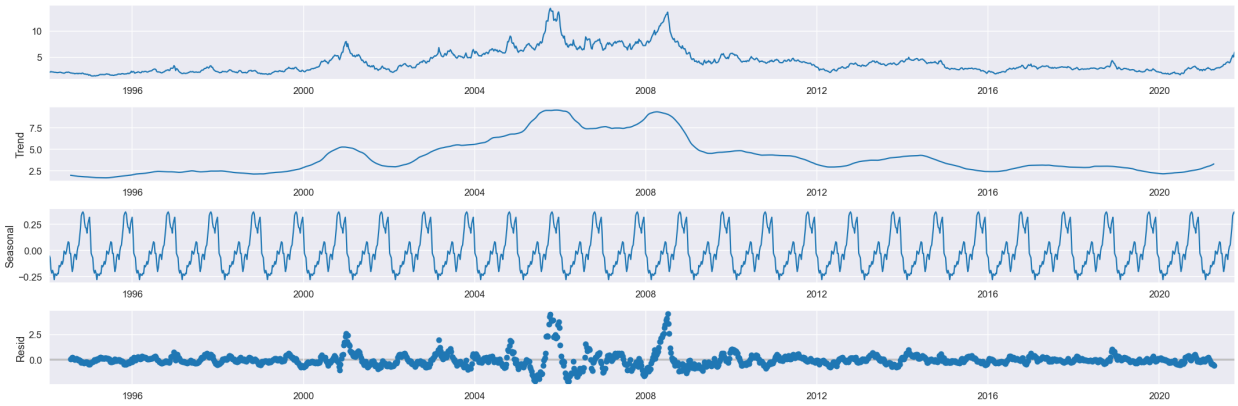
executed in 236ms, finished 09:18:24 2021-10-22



The rolling standard deviation again shows the increase in variability when the mean increases. The mean is certainly not constant and this data is not stationary.

In [52]:
```
#Examine components of import data
plt.rcParams['figure.figsize'] = 30,10
decompose = seasonal_decompose(gas_weekly, model='additive').plot()
```

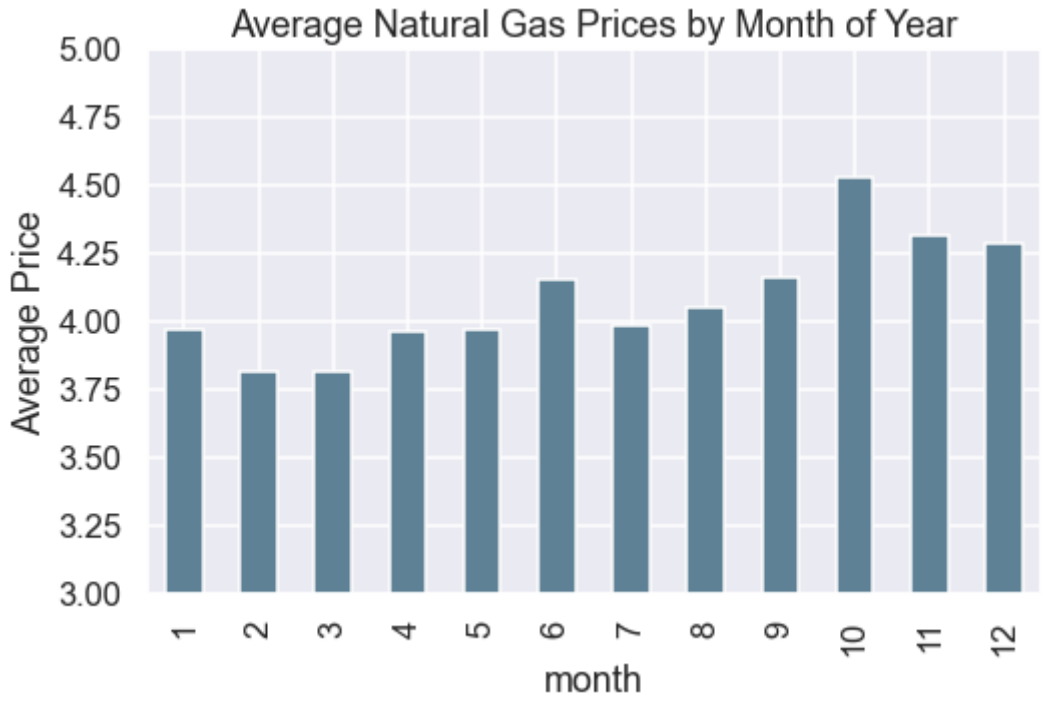
executed in 700ms, finished 09:18:25 2021-10-22



An additive model was used because the variance is not increasing over time. A seasonal trend is shown, which makes sense that gas prices would be higher during certain months due to demand.

In [53]:
```
gas_month = gas_weekly.copy()
gas_month['month'] = gas_month.index.month
gas_month = gas_month.groupby('month').mean()
gas_month.plot(
    kind='bar',
    figsize=(8,5),
    color=NEUTRAL,
    legend=None
)
plt.ylim(3,5)
plt.title('Average Natural Gas Prices by Month of Year')
plt.ylabel('Average Price');
```

executed in 159ms, finished 09:18:25 2021-10-22

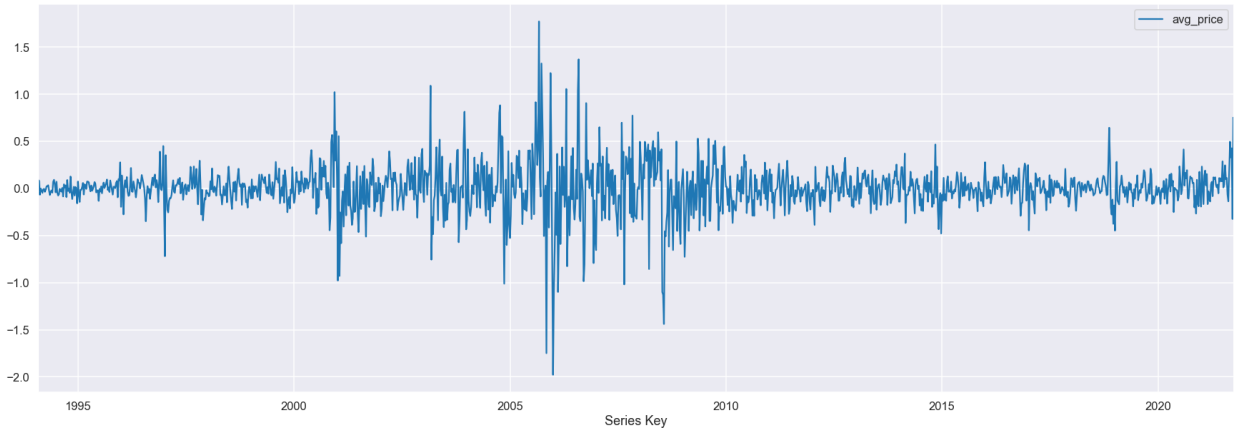


In looking at the average gas prices by month of the year, prices are the highest in October - December.

In [54]:
```
#Plot the first difference of the gas data.
gas_diff = gas_weekly.diff().dropna()
gas_diff.plot()
```

executed in 289ms, finished 09:18:26 2021-10-22

Out[54]: <AxesSubplot:xlabel='Series Key'>

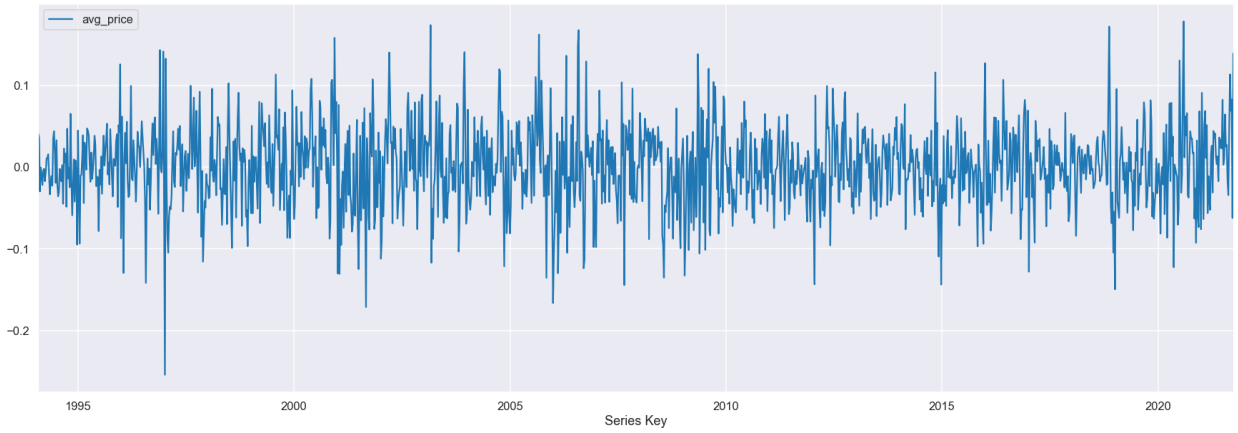


Taking the first difference made the mean more constant, but the standard deviation is still not constant.

In [55]:
```
#Plot the first difference of the logged gas data
gas_log = np.log(gas_weekly).diff().dropna()
gas_log.plot()
```

executed in 455ms, finished 09:18:26 2021-10-22

Out[55]: <AxesSubplot:xlabel='Series Key'>



This definitely appears to be more stationary, and that is confirmed with the Dickey-Fuller test.

In [56]:
```
print(f'p-value original data: {adfuller(gas_weekly)[1]}')
print(f'p-value differenced data: {adfuller(gas_diff)[1]}')
print(f'p-value differenced and logged data: {adfuller(gas_log)[1]}')
```

executed in 95ms, finished 09:18:26 2021-10-22

```
p-value original data: 0.06383113022106938
p-value differenced data: 1.0446890140370101e-22
p-value differenced and logged data: 0.0
```

Logged data will be used because that improved the stationarity.

In [57]:
```
#Split the data so that the test set contains 145 weeks of data and the tra
#set has 1302 weeks.
gas_weekly.columns = ['price']
logged_gas = np.log(gas_weekly)
gas_split = int(logged_gas.shape[0]*.90)
gas_train = logged_gas[:gas_split]
gas_test = logged_gas[gas_split:]

gas_test.shape, gas_train.shape
```

executed in 5ms, finished 09:18:26 2021-10-22

Out[57]: ((145, 1), (1302, 1))

4.3 Decrease Strain on Power Grid During High Demand Periods

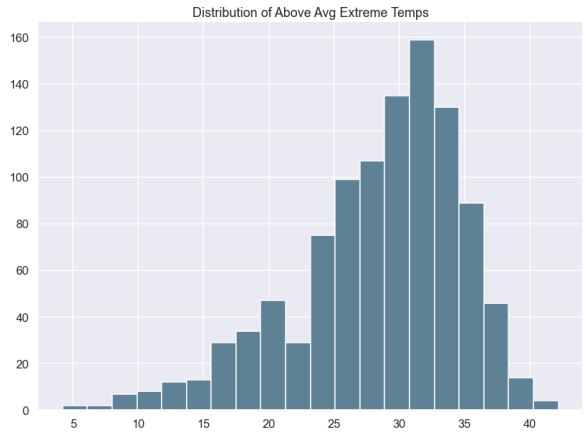
In [58]:
```
#Select only the relevant columns.
demand_above_df = demand_above[['extreme','demand']]
demand_below_df = demand_below[['extreme', 'demand']]

demand_above_df.shape, demand_below_df.shape
```

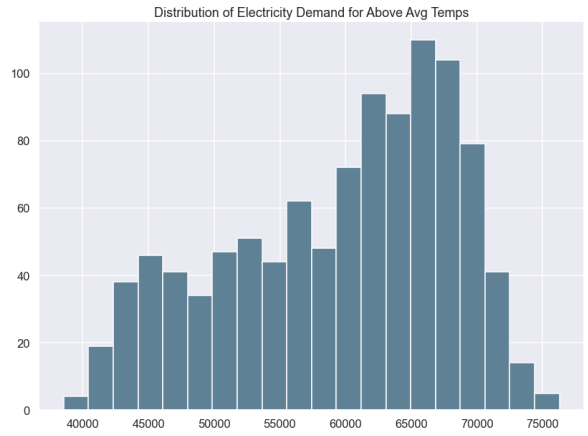
executed in 5ms, finished 09:18:26 2021-10-22

Out[58]: ((1041, 2), (1005, 2))

In [59]:
```
#Plot the histograms for the temperatures and energy demand on days with ab
#average temperatures.
fig,(ax1,ax2) = plt.subplots(1,2)
ax1.hist(
    demand_above_df['extreme'],
    bins=20,
    color=NEUTRAL
)
ax1.set_title('Distribution of Above Avg Extreme Temps')
ax2.hist(
    demand_above_df['demand'],
    bins=20,
    color=NEUTRAL
)
ax2.set_title('Distribution of Electricity Demand for Above Avg Temps');
```

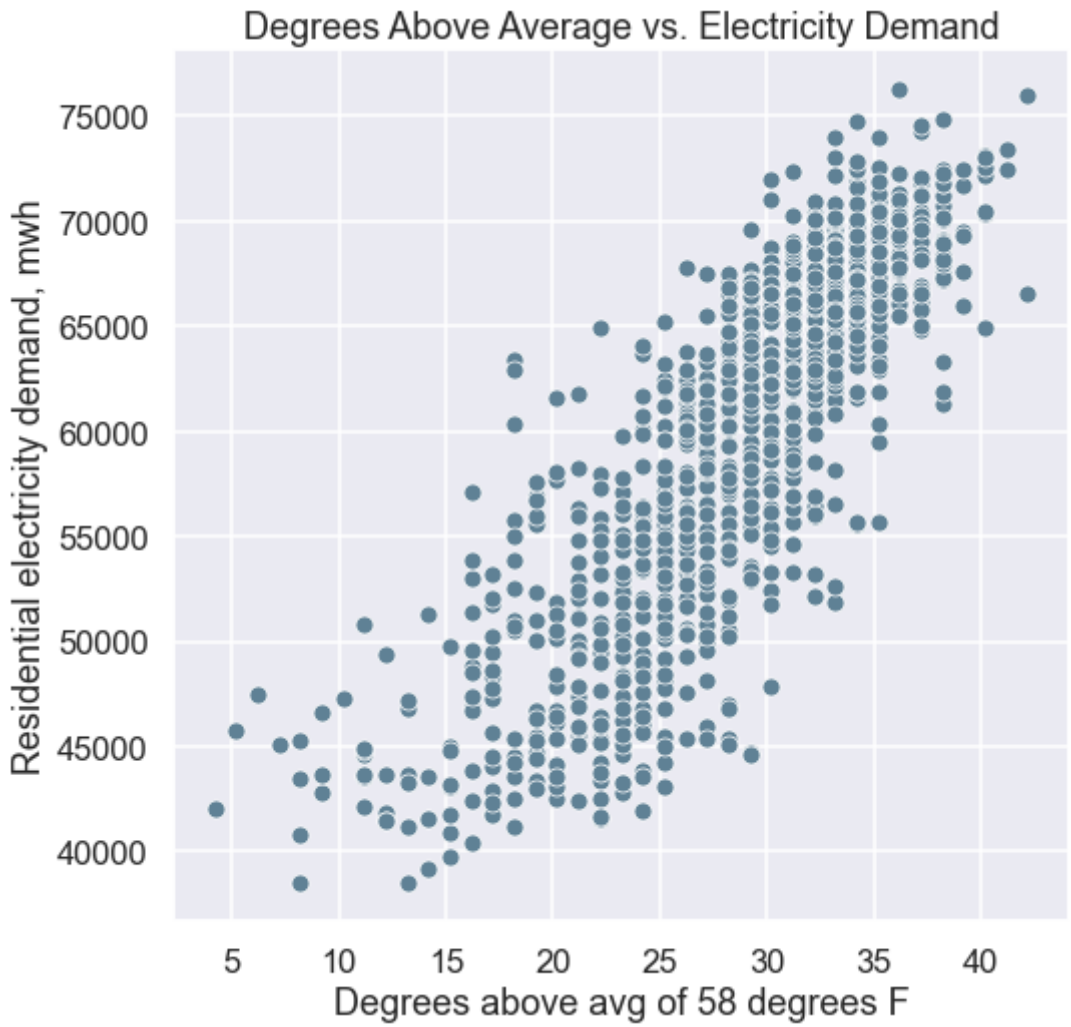
executed in 331ms, finished 09:18:26 2021-10-22





In [61]:
```
#Plot the scatterplot for demand vs degrees above average.
plt.subplots(figsize=(8,8))
sns.scatterplot(
    data=demand_above_df,
    x='extreme',
    y='demand',
    color=NEUTRAL
)
plt.title('Degrees Above Average vs. Electricity Demand')
plt.xlabel('Degrees above avg of 58 degrees F')
plt.ylabel('Residential electricity demand, mwh');
```

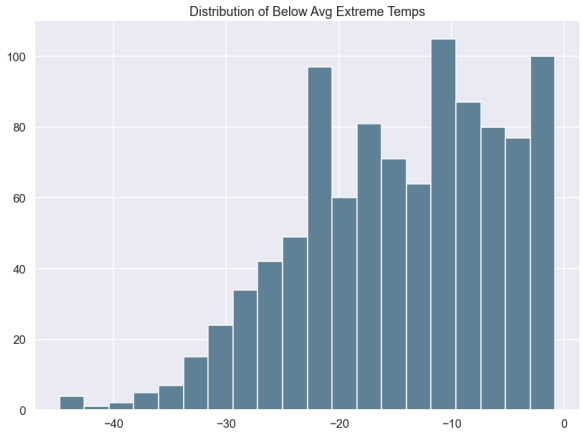
executed in 390ms, finished 09:32:23 2021-10-22

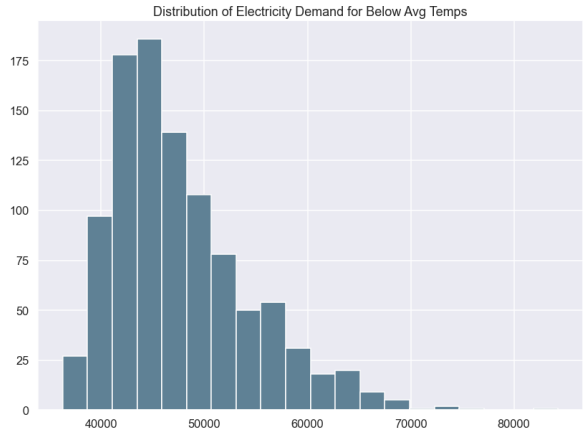


The data are definitely linear and have somewhat normal distributions, although both are slightly skewed left and demand is platykurtic.

In [62]:
```
#Plot the histograms for the temperatures and energy demand on days with be
#average temperatures.
fig,(ax1,ax2) = plt.subplots(1,2)
ax1.hist(
    demand_below_df['extreme'],
    bins=20,
    color=NEUTRAL
)
ax1.set_title('Distribution of Below Avg Extreme Temps')
ax2.hist(
    demand_below_df['demand'],
    bins=20,
    color=NEUTRAL
)
ax2.set_title('Distribution of Electricity Demand for Below Avg Temps');
```

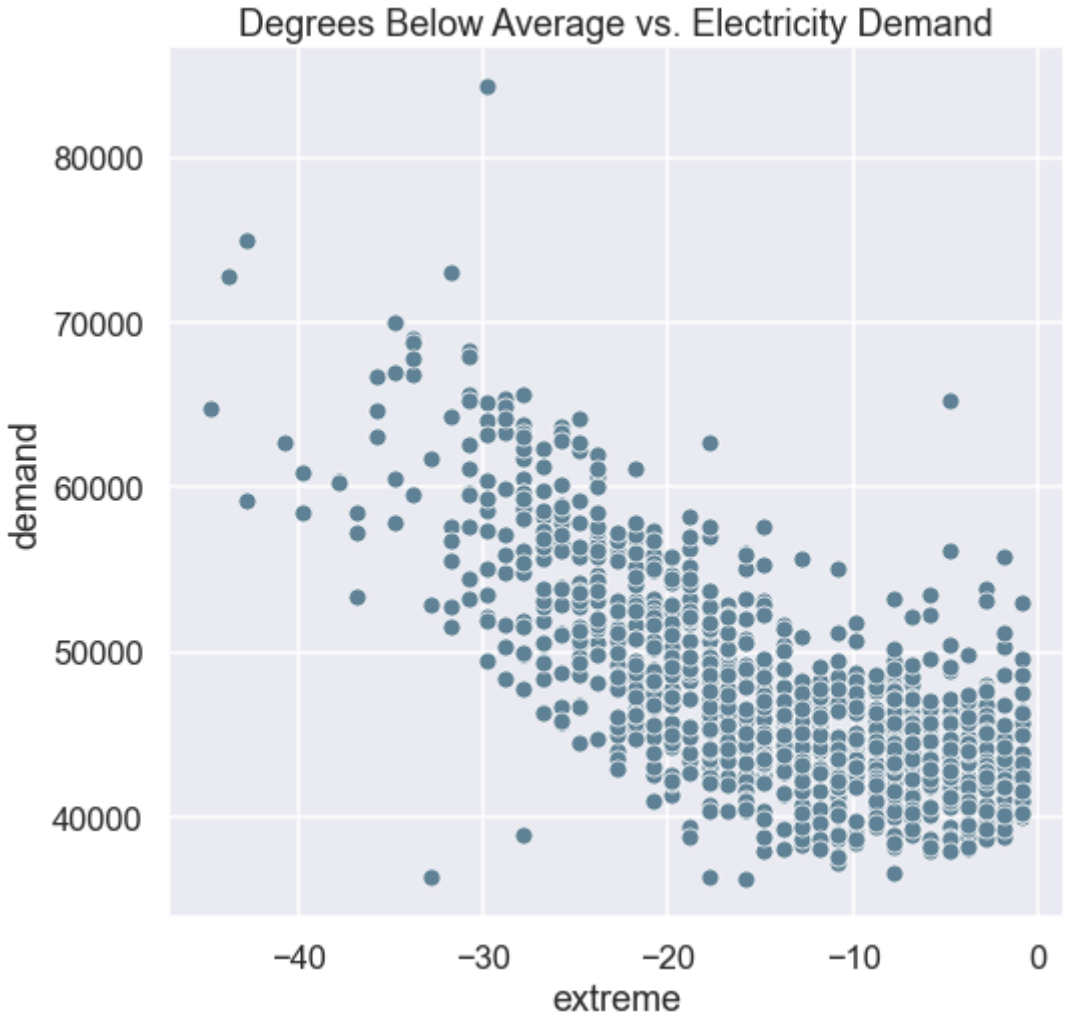
executed in 299ms, finished 09:32:32 2021-10-22





In [63]:
```
#Plot the scatterplot for demand vs degrees below average.
plt.subplots(figsize=(8,8))
sns.scatterplot(
    data=demand_below_df,
    x='extreme',
    y='demand',
    color=NEUTRAL
)
plt.title('Degrees Below Average vs. Electricity Demand');
```

executed in 170ms, finished 09:32:32 2021-10-22



This relationship is not as linear and the data is less normally distributed.

In [193]:
```
def build_train_val_test(df, x='extreme', y='demand'):
    """Takes in a data frame and the feature and target column names and
    returns train, validation and test sets."""

    X = df.drop(y, axis=1)
    y = df[y]

    X_train, X_, y_train, y_ = train_test_split(X, y, test_size=0.3)
    X_val, X_test, y_val, y_test = train_test_split(X_, y_, test_size=0.5)

    print(f'X shapes: train, val, test:\
    {X_train.shape},{X_val.shape},{X_test.shape}')
    print(f'y shapes: train, val, test:\
    {y_train.shape},{y_val.shape},{y_test.shape}')

    return X_train, X_val, X_test, y_train, y_val, y_test
```

executed in 4ms, finished 10:19:25 2021-10-22

In [194]:
```
#Split the data for both above and below-average temperatures into train,
#validation and test sets.

(X_train_above,
 X_val_above,
 X_test_above,
 y_train_above,
 y_val_above,
 y_test_above) = build_train_val_test(demand_above_df)

(X_train_below,
 X_val_below,
 X_test_below,
 y_train_below,
 y_val_below,
 y_test_below) = build_train_val_test(demand_below_df)
```

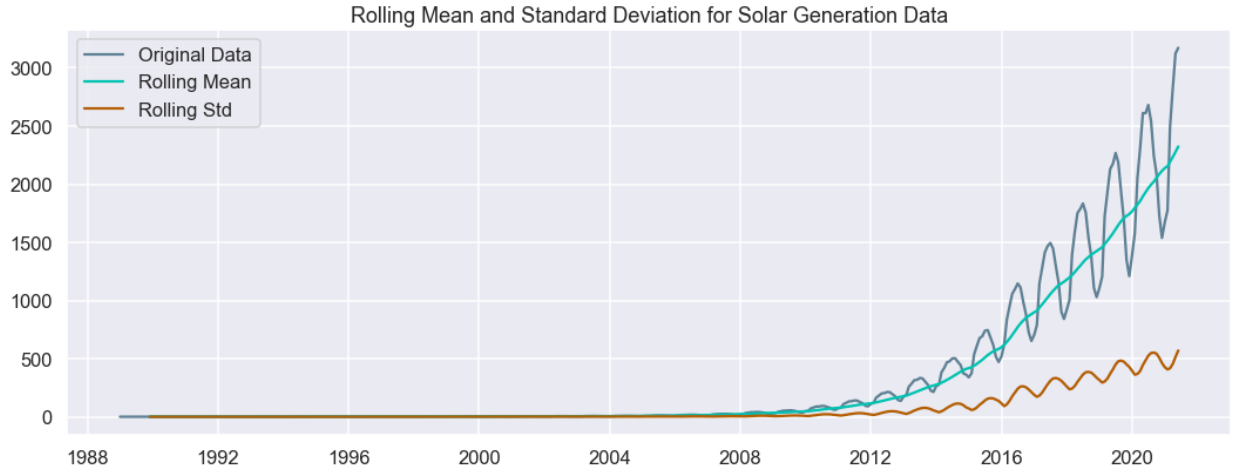
executed in 8ms, finished 10:19:35 2021-10-22

```
X shapes: train, val, test:    (728, 3),(156, 3),(157, 3)
y shapes: train, val, test:    (728,),(156,),(157,)
X shapes: train, val, test:    (703, 1),(151, 1),(151, 1)
y shapes: train, val, test:    (703,),(151,),(151,)
```

4.4 Stay Competitive With U.S. Market

In [66]:
```
#Check the rolling mean and standard deviation of solar generation
plot_rolling(us_solar, 12, 'Solar Generation');
```

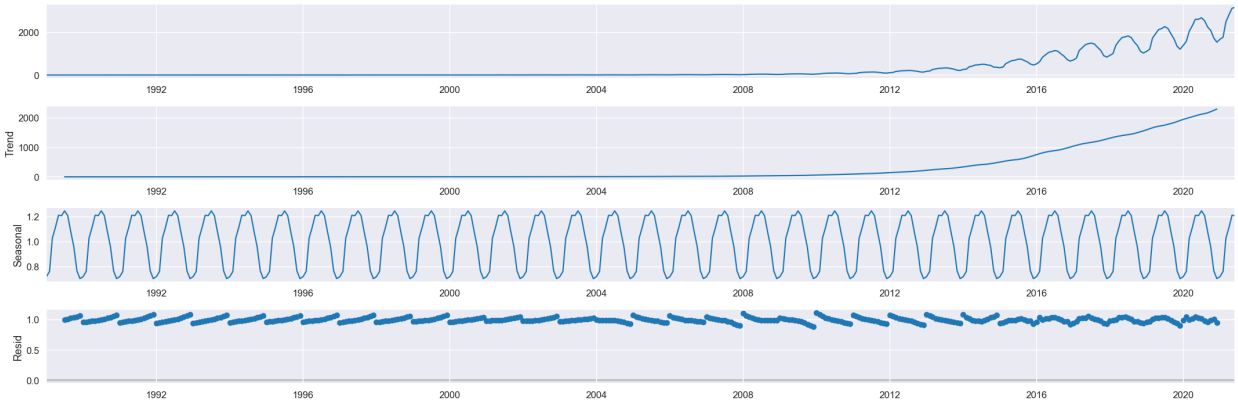
executed in 250ms, finished 09:32:32 2021-10-22



Both the mean and standard deviation are increasing. The data is non-stationary.

In [67]:
```
#Examine components of solar data
plt.rcParams['figure.figsize'] = 30,10
decompose = seasonal_decompose(us_solar, model = 'multiplicative').plot()
```

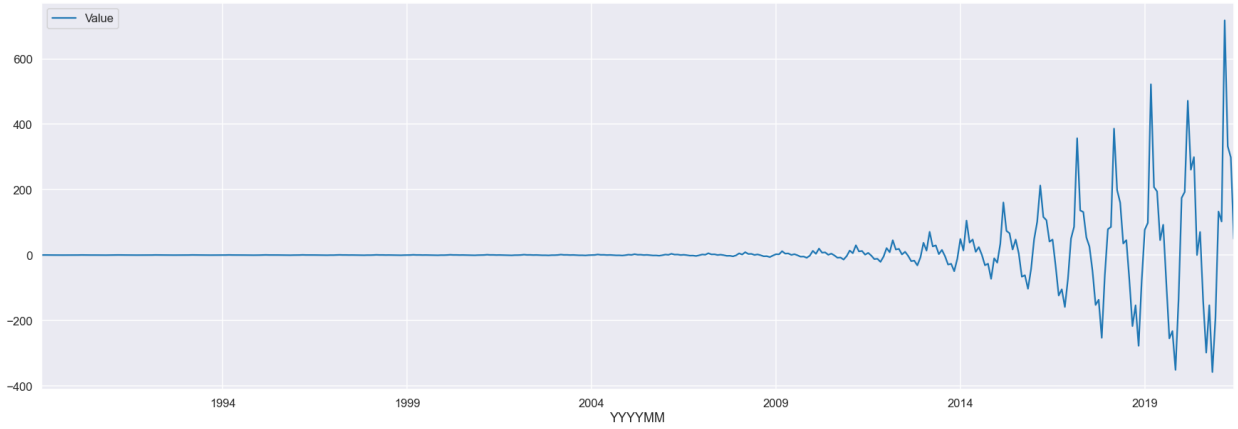
executed in 777ms, finished 09:32:33 2021-10-22



There is a clear positive trend and seasonality.

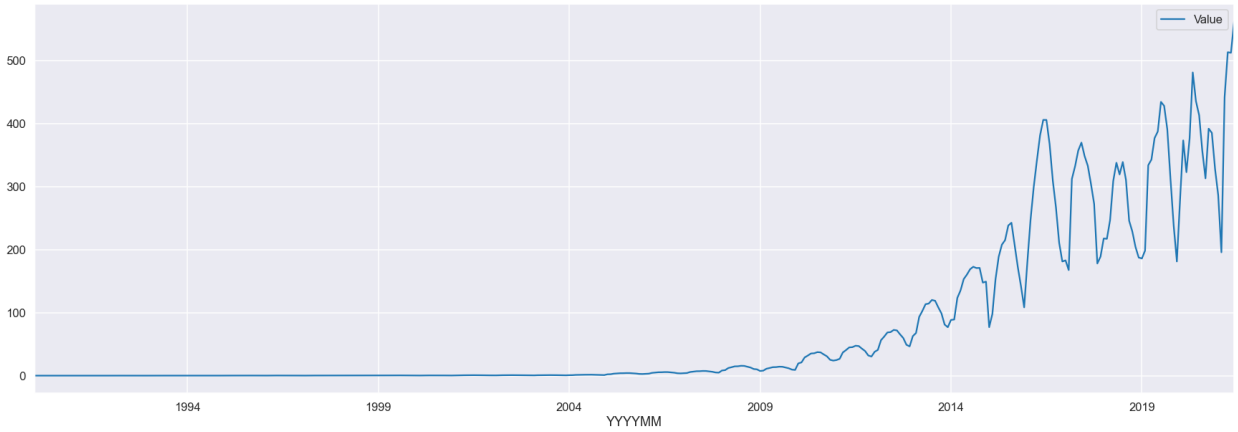
In [68]:
```
#Plot the first difference
solar_diff = us_solar.diff().dropna().plot(figsize=(30,10))
```

executed in 298ms, finished 09:32:33 2021-10-22



In [69]:
```
#Plot the annual difference (period=12)
solar_annual_diff = us_solar.diff(12).dropna().plot(figsize=(30,10))
```

executed in 306ms, finished 09:32:34 2021-10-22

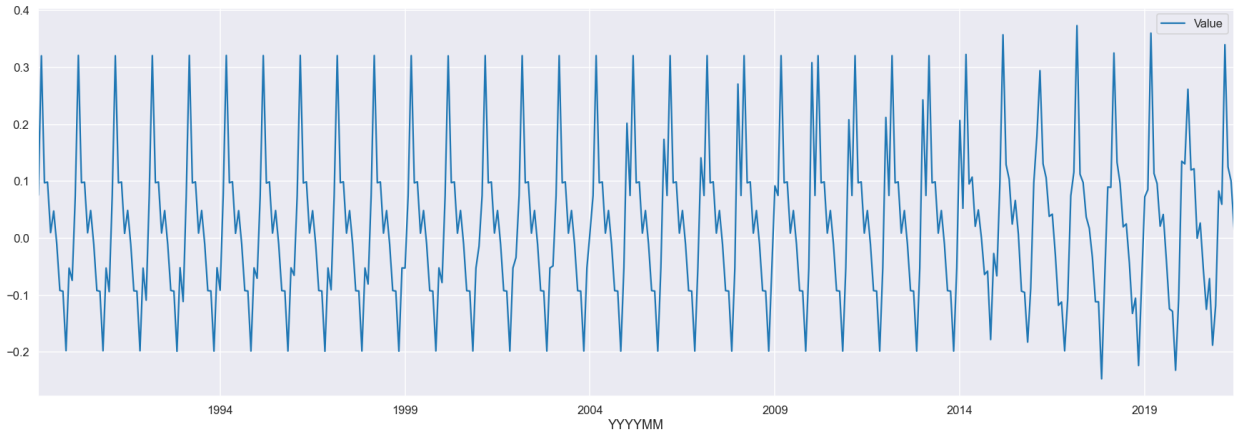


Plotting the 1st and 12th differences show only a slight improvement in stationarity.

In [70]:
```
#Plot the first difference of the logged solar data.
np.log(us_solar).diff().dropna().plot(figsize=(30,10))
```

executed in 307ms, finished 09:32:34 2021-10-22

Out[70]: <AxesSubplot:xlabel='YYYYMM'>



Taking both the log and the first difference seems to greatly improve the stationarity; however, clear seasonality is still apparent.

In [203]:
```
print(f'p-value original data: {adfuller(us_solar)[1]}')
print(f'p-value differenced data: {adfuller(us_solar.diff().dropna())[1]}')
print(f'p-value logged and differenced data:\
{adfuller(np.log(us_solar).diff().dropna())[1]}')
print(f'p-value logged and annually differenced data:\
{adfuller(np.log(us_solar).diff(12).dropna())[1]}')
```

executed in 45ms, finished 10:22:37 2021-10-22

```
p-value original data: 0.9989484564402845
p-value differenced data: 0.9967076789673472
p-value logged and differenced data:0.3448153235617447
p-value logged and annually differenced data:0.6494754796181746
```

The Dickey-Fuller test confirms that the logged and first-differenced data is the most stationary, although the p-value greater than 0.05 confirms that it is not stationary.

In [72]:
```
#Split the data so that there are 12 years in the training set and just und
#two years in the test set.
us_solar.columns = ['actual']
solar_split = '2019-12-01'
log_solar = np.log(us_solar)
solar_train = log_solar[:solar_split]
solar_test = log_solar[solar_split:]

solar_train.shape, solar_test.shape
```

executed in 6ms, finished 09:32:34 2021-10-22

Out[72]:
```
((372, 1), (19, 1))
```

5 Modeling

5.1 Helper Functions for Time Series

In [73]:
```
def grid_search(train, max_value, season, trend = None):
    """Takes in training data, the max value for p,d,q and a season,
    performs a grid search of the hyperparameters and returns the values wi
    the lowest AIC score."""

    p = d = q = range(0, max_value+1)

    pdq = [(ar, diff, ma) for ar in p for diff in d for ma in q]
    pdqs = [(c[0], c[1], c[2], season) for c in pdq]

# Iterate and try models.

    combo, value = (None, None)
    for pdq_combo in pdq:
        for pdqs_combo in pdqs:
            model = SARIMAX(
            train,
            order=pdq_combo,
            seasonal_order=pdqs_combo,
            enforce_stationarity=False,
            enforce_invertibility=False,
            trend = trend
            )
            output = model.fit()

        if value is None or output.aic < value:
            combo, value = ((pdq_combo, pdqs_combo), output.aic)
        return combo, value
```

executed in 4ms, finished 09:32:34 2021-10-22

In [74]:
```
def get_fit(params, train):
    """Takes in the hyperparameters from grid_search and the train data and
    returns a fitted SARIMAX model."""

    or_params = params[0][0]
    so_params = params[0][1]
    model = SARIMAX(
        train,
        order=or_params,
        seasonal_order=so_params,
        enforce_stationarity=False,
        enforce_invertibility=False
    )
    fitted_model = model.fit()
    return fitted_model
```

executed in 3ms, finished 09:32:34 2021-10-22

In [75]:
```
def predict_and_score(fitted_model, test):
    """Takes in a fitted SARIMAX model and a test set, prints the RMSE and
    returns the precitions and the RMSE."""

    predictions = fitted_model.forecast(steps=test.shape[0])
    rmse = round(np.sqrt(mean_squared_error(test, predictions)),3)
    print(f'The RMSE is {rmse}.')
    return predictions, rmse
```

executed in 3ms, finished 09:32:34 2021-10-22

In [76]:
```
def diagnostic_plot(fitted_model):
    """Takes in a fitted model and returns the plot diagnostics."""

    plt.rc("figure", figsize=(16,10))
    plt.tight_layout()
    diagnostics = fitted_model.plot_diagnostics()
    return diagnostics
```

executed in 2ms, finished 09:32:34 2021-10-22

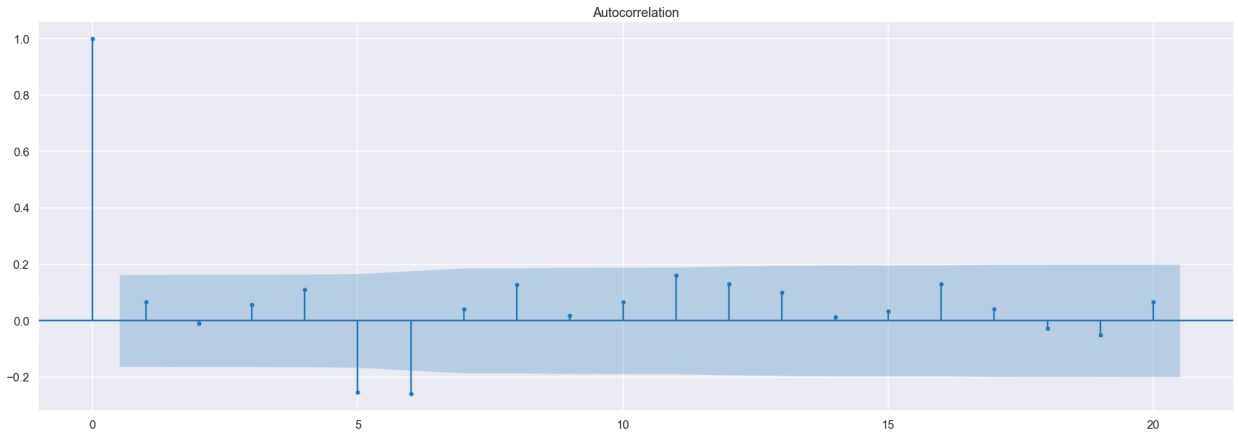
In [77]:
```
def plot_forecast(train, test, fitted_model, steps, title, ylabel):
    """Takes in a train set, test set, fitted model, number of steps, title
    and ylabel and constructs a forecast of step length and plots the actua
    data along with the forecasted data. Returns the forecast and the figur
    """

    fig, ax = plt.subplots(figsize=(15, 5))

    # Plot the data
    train.plot(
        ax=ax,
        color=DARK_NEUTRAL,
        label='actual (train)'
    )
    test.plot(
        ax=ax,
        color=NEUTRAL,
        label='actual (test)'
    )

    # Construct the forecasts
    fcast = fitted_model.get_forecast(
        steps=steps,
        dynamic=True).summary_frame()
    fcast['mean'].plot(
        ax=ax,
        style='k--',
        label='forecasted')
    ax.fill_between(
        fcast.index,
        fcast['mean_ci_lower'],
        fcast['mean_ci_upper'],
        color=HIGHLIGHT,
        alpha=0.1);
    plt.xlabel(
        'Date',
        weight='bold'
    )
    plt.ylabel(
        ylabel,
        weight='bold'
    )
    plt.title(
        f'Forecasted {title}',
        weight='bold',
        size='large'
    )
    ax.legend()
    return fcast, (fig,ax)
```

executed in 4ms, finished 09:32:34 2021-10-22

5.2 Reduce Dependence on Imported Electricity

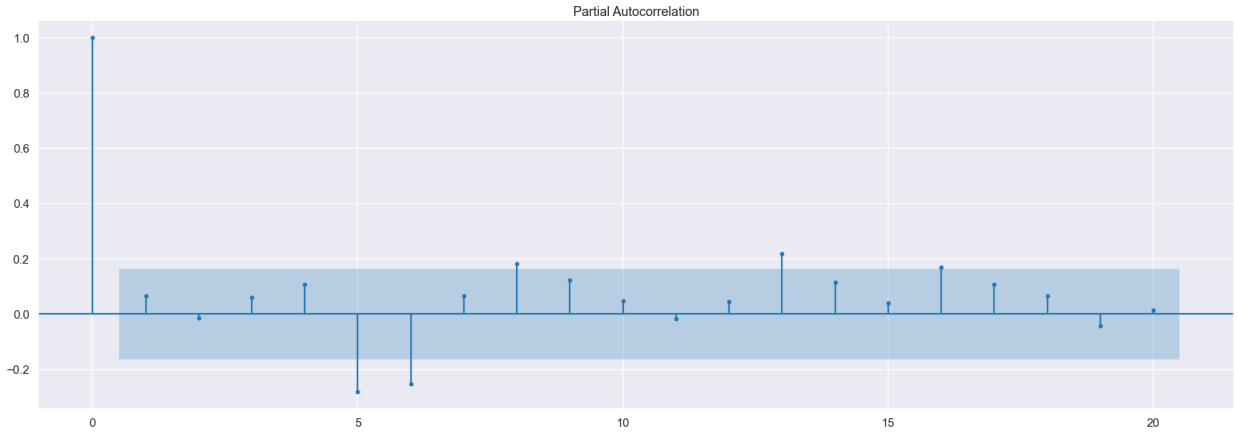
In [78]:
```
#Examine the autocorrelation function for the differenced customers data.
acf_demand_diff = plot_acf(demand_train.diff().dropna(), lags=20)
```

executed in 158ms, finished 09:32:34 2021-10-22



In [79]:
```
pacf_demand_diff = plot_pacf(demand_train.diff().dropna(), lags=20)
```

executed in 172ms, finished 09:32:35 2021-10-22



Based on the acf and pacf plots, there may be a significant AR and/or MA value at lag 5 or 6.

5.2.1 Naive Model

In [80]:
```
#Create a naive model that predicts the train mean.
naive_pred = [demand_train.mean() for n in range(len(demand_test))]
naive_rmse = round(np.sqrt(mean_squared_error(demand_test, naive_pred)),3)
print(f'The naive RMSE is {naive_rmse}.')
```

executed in 5ms, finished 09:32:35 2021-10-22

```
The naive RMSE is 0.085.
```

5.2.2 Simple AR Model (With a First Difference)

In [81]:
```
#AR model with a lag of 5 and a first difference.
AR_model = SARIMAX(
    demand_train,
    order = (5,1,0)
)
AR_fit = AR_model.fit()
AR_fit.summary()
```

executed in 143ms, finished 09:32:35 2021-10-22

Out[81]:

SARIMAX Results

Dep. Variable:	total_kwh	**No. Observations:**	144
Model:	SARIMAX(5, 1, 0)	**Log Likelihood**	713.117
Date:	Fri, 22 Oct 2021	**AIC**	-1414.234
Time:	09:32:35	**BIC**	-1396.457
Sample:	01-01-2008	**HQIC**	-1407.011
	- 12-01-2019		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.1730	0.056	3.078	0.002	0.063	0.283
ar.L2	0.0859	0.090	0.953	0.340	-0.091	0.262
ar.L3	0.1369	0.095	1.437	0.151	-0.050	0.324
ar.L4	0.2061	0.080	2.584	0.010	0.050	0.362
ar.L5	-0.1898	0.045	-4.212	0.000	-0.278	-0.101
sigma2	2.719e-06	1.4e-07	19.425	0.000	2.44e-06	2.99e-06

Ljung-Box (L1) (Q):	1.11	**Jarque-Bera (JB):**	1269.41
Prob(Q):	0.29	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.27	**Skew:**	-2.10
Prob(H) (two-sided):	0.00	**Kurtosis:**	16.98

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [82]:
```
AR_pred, AR_rmse = predict_and_score(AR_fit, demand_test)
```

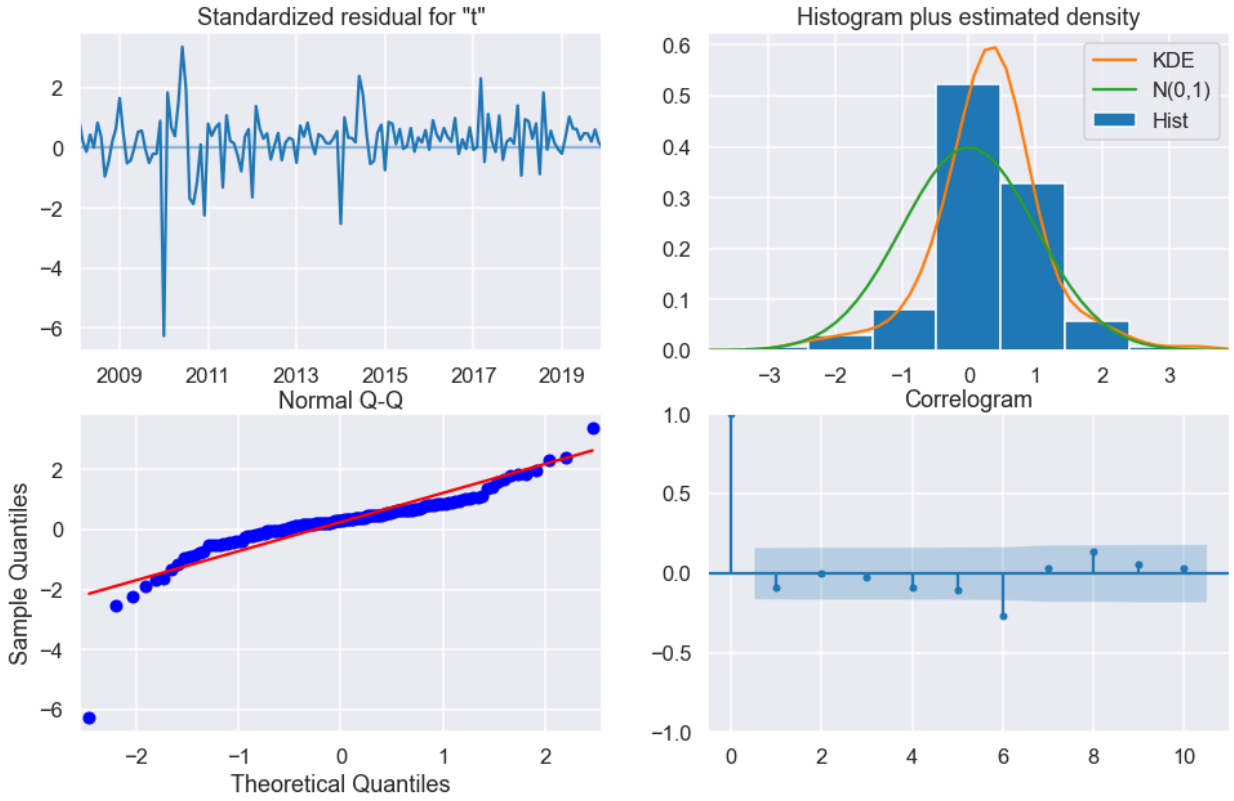
executed in 11ms, finished 09:32:35 2021-10-22

```
The RMSE is 0.022.
```

In [83]:
```
AR_diagnostic = diagnostic_plot(AR_fit)
```

executed in 730ms, finished 09:32:35 2021-10-22

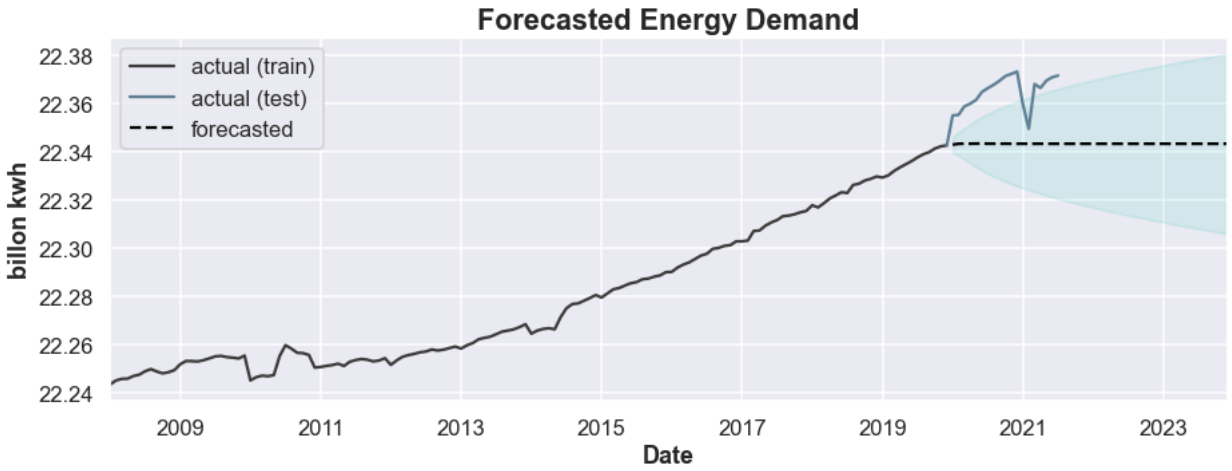
```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/gra
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)


<Figure size 1152x720 with 0 Axes>
```



The residuals have a leptokurtic distribution, which is likely from the Covid-related variability that the model did not account for. The correlogram suggests that the model is accounting for most of the information in the data; however, the significant lag at 6 indicate that there may be some seasonality that is not being addressed.

In [84]:
```
AR_fcast, AR_fcast_plt = plot_forecast(
    demand_train,
    demand_test,
    AR_fit,
    48,
    'Energy Demand',
    'billon kwh')
```

executed in 242ms, finished 09:32:36 2021-10-22



Based on the predictions, it is clear that the model is not capturing the increasing trend.

5.2.3 AR Model With Trend

In [85]:
```
#AR model with linear trend hyperparamter added.
ARt_model = SARIMAX(
    demand_train,
    order = (5,1,0),
    trend='t'
)
ARt_fit = ARt_model.fit()
ARt_fit.summary()
```

executed in 296ms, finished 09:32:36 2021-10-22

ar.L2	-0.0520	0.141	-0.370	0.712	-0.328	0.224
ar.L3	-0.0081	0.128	-0.064	0.949	-0.258	0.242
ar.L4	0.0703	0.122	0.575	0.565	-0.169	0.310
ar.L5	-0.3163	0.046	-6.897	0.000	-0.406	-0.226
sigma2	2.345e-06	1.1e-07	21.288	0.000	2.13e-06	2.56e-06

Ljung-Box (L1) (Q):	1.46	**Jarque-Bera (JB):**	1779.87
Prob(Q):	0.23	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.20	**Skew:**	-2.39
Prob(H) (two-sided):	0.00	**Kurtosis:**	19.61

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [86]:
```
ARt_pred, ARt_rmse = predict_and_score(ARt_fit, demand_test)
```

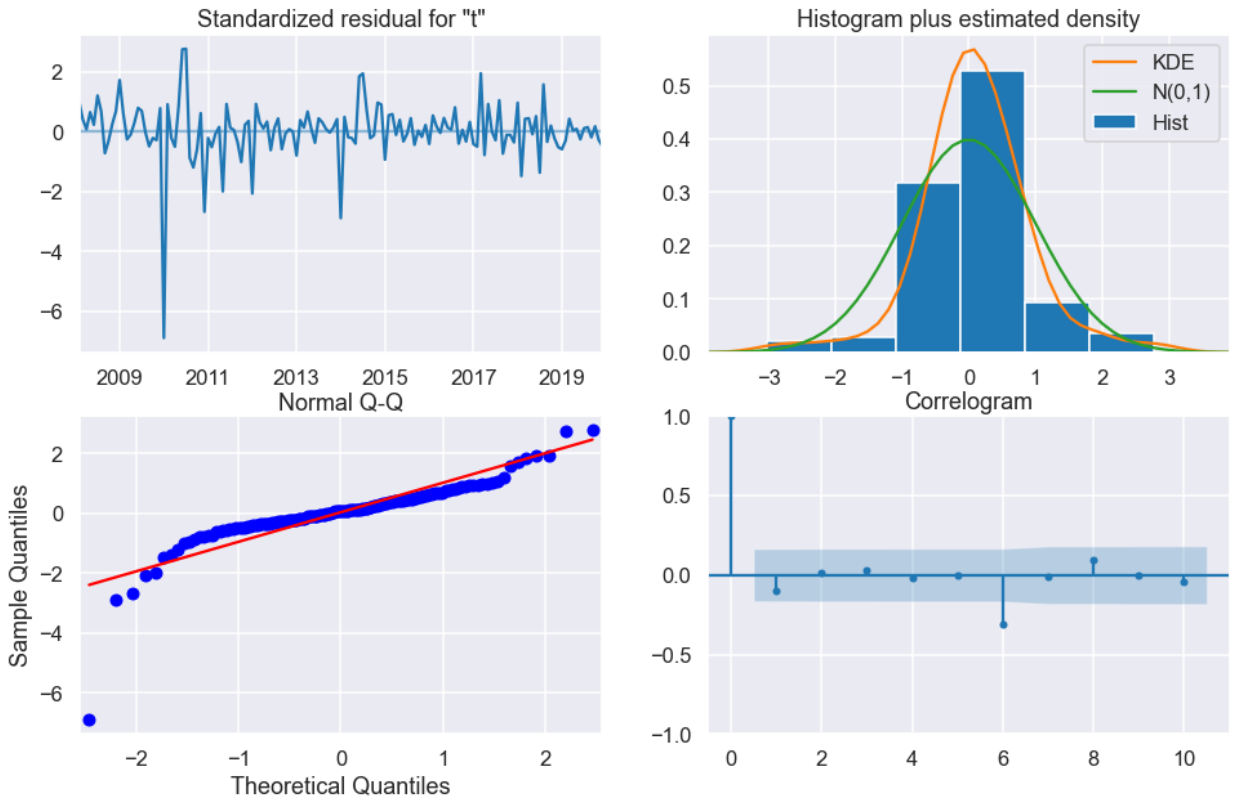
executed in 15ms, finished 09:32:36 2021-10-22

```
The RMSE is 0.01.
```

In [87]:
```
ARt_diagnostic = diagnostic_plot(ARt_fit)
```

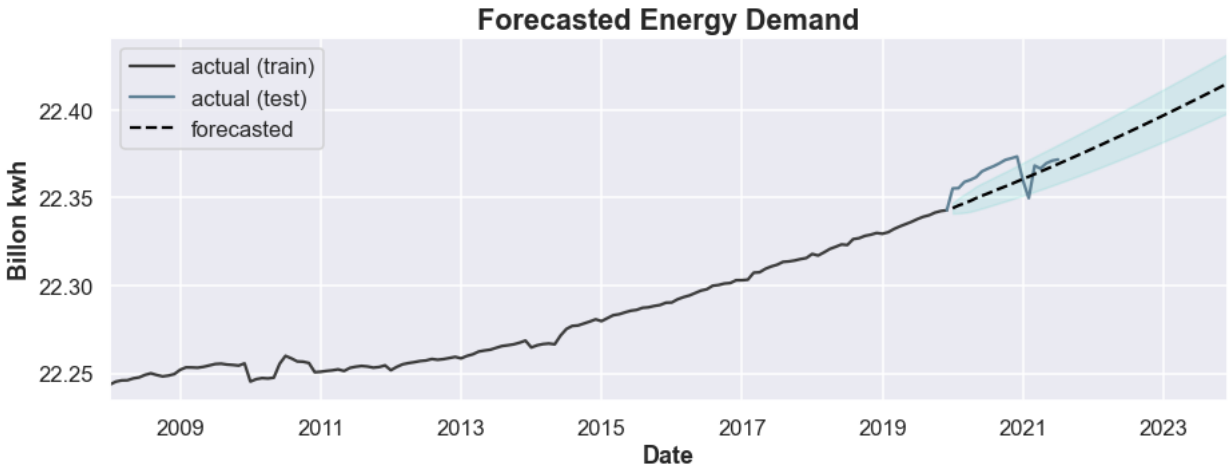
executed in 619ms, finished 09:32:37 2021-10-22

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/gra
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)

<Figure size 1152x720 with 0 Axes>
```



In [88]:
```
ARt_fcast, ARt_fcast_plt = plot_forecast(
    demand_train,
    demand_test,
    ARt_fit,
    48,
    'Energy Demand',
    'Billon kwh')
```

executed in 240ms, finished 09:32:37 2021-10-22



The diagnostics still show that there is information that the model is not capturing. This is also clear on the forecast plot, where the temporary increase in residential demand is not picked up by the model. However, the model appears to do quite well at generalizing the overall trend.

The only significant AR value is at lag 5, indicating that the demand 5 months ago is predictive of the demand in the current month.

5.2.4 SARIMA Model Without Trend

In [89]:
```
#Run a grid search for hyperparameters if the file is not in the directory.
if 'demand_params.joblib' in os.listdir('files'):
    demand_params = joblib.load('files/demand_params.joblib')
else:
    demand_params = grid_search(demand_train, 5, 12)
    joblib.dump(demand_params, 'files/demand_params.joblib')
```

executed in 5ms, finished 09:32:37 2021-10-22

In [90]:
```
#Fit and summarize the model
SARIMA_fit = get_fit(demand_params, demand_train)
SARIMA_fit.summary()
```

executed in 44.8s, finished 09:33:22 2021-10-22

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/tsa/statespace/sarimax.py:865: UserWarning: Too few observations to estimate starting parameters for seasonal ARMA. All parameters except for variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/base/model.py:566: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Out[90]:

SARIMAX Results

Dep. Variable:	total_kwh	**No. Observations:**	144
Model:	SARIMAX(5, 5, [1, 2, 3, 4, 5], 12)	**Log Likelihood**	61.843
Date:	Fri, 22 Oct 2021	**AIC**	-101.686
Time:	09:33:22	**BIC**	-89.195
Sample:	01-01-2008	**HQIC**	-98.544
	- 12-01-2019		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.S.L12	0.0002	1.079	0.000	1.000	-2.115	2.115
ar.S.L24	-0.0003	1.899	-0.000	1.000	-3.722	3.721
ar.S.L36	-0.0002	1.804	-8.78e-05	1.000	-3.536	3.536
ar.S.L48	-0.0004	1.147	-0.000	1.000	-2.248	2.247
ar.S.L60	-0.0004	0.528	-0.001	0.999	-1.036	1.035
ma.S.L12	0.0006	0.253	0.003	0.998	-0.495	0.496
ma.S.L24	0.0001	0.512	0.000	1.000	-1.004	1.004
ma.S.L36	0.0002	0.354	0.000	1.000	-0.693	0.693
ma.S.L48	-1.489e-05	0.067	-0.000	1.000	-0.132	0.132
ma.S.L60	-9.37e-05	0.029	-0.003	0.997	-0.057	0.056
sigma2	1.849e-06	1.24e-06	1.490	0.136	-5.83e-07	4.28e-06

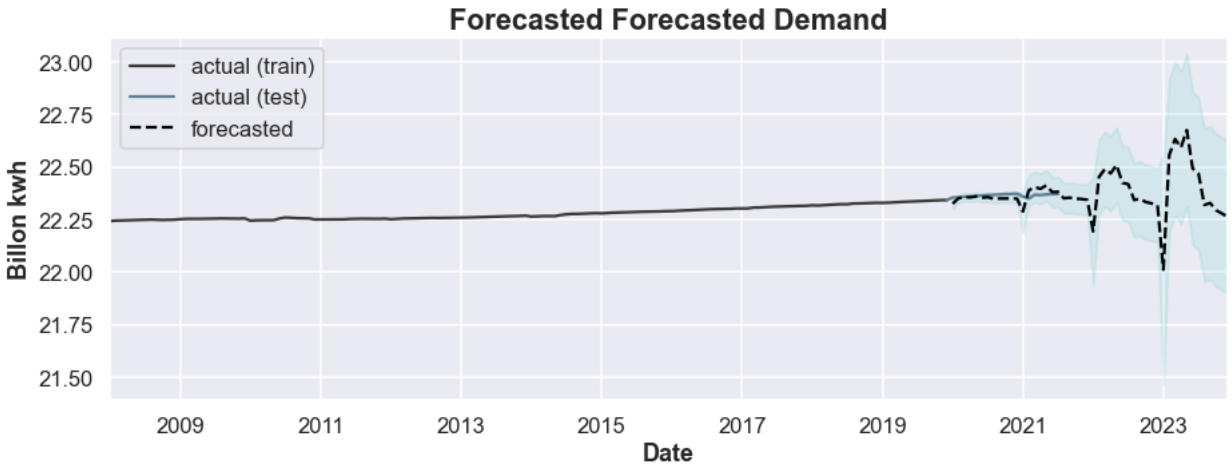
Ljung-Box (L1) (Q):	13.65	**Jarque-Bera (JB):**	2.19
Prob(Q):	0.00	**Prob(JB):**	0.33
Heteroskedasticity (H):	0.16	**Skew:**	-0.65
Prob(H) (two-sided):	0.02	**Kurtosis:**	2.22

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.43e+19. Standard errors may be unstable.

In [91]:
```
#Score the model
SARIMA_pred, SARIMA_rmse = predict_and_score(SARIMA_fit, demand_test)
```
executed in 33ms, finished 09:33:22 2021-10-22

```
The RMSE is 0.029.
```

In [92]:
```
#Plot the forecast
SARIMA_fcast, SARIMA_fcast_plt = plot_forecast(
    demand_train,
    demand_test,
    SARIMA_fit,
    48,
    'Forecasted Demand',
    'Billon kwh')
```
executed in 385ms, finished 09:33:22 2021-10-22



The p-values for the coefficients are at or near 1, indicating that they are not significant. The forecast also shows that the model is not generalizing well.

5.2.5 SARIMA Model With Trend

In [93]:
```
if 'demandtr_params.joblib' in os.listdir('files'):
    demandtr_params = joblib.load('files/demandtr_params.joblib')
else:
    demandtr_params = grid_search(demand_train, 5, 12, trend='t')
    joblib.dump(demandtr_params, 'files/demandtr_params.joblib')
```
executed in 5ms, finished 09:33:22 2021-10-22

In [94]:
```
SARIMAtr_fit = get_fit(demandtr_params, demand_train)
SARIMAtr_fit.summary()
```

executed in 44.0s, finished 09:34:06 2021-10-22

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/tsa/statespace/sarimax.py:865: UserWarning: Too few observations to estimate starting parameters for seasonal ARMA. All parameters except for variances will be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/base/model.py:566: ConvergenceWarning: Maximum Likelihood optimization failed to converge. Check mle_retvals
  warnings.warn("Maximum Likelihood optimization failed to "
```

Out[94]:

SARIMAX Results

Dep. Variable:	total_kwh	**No. Observations:**	144
Model:	SARIMAX(5, 5, [1, 2, 3, 4, 5], 12)	**Log Likelihood**	61.843
Date:	Fri, 22 Oct 2021	**AIC**	-101.686
Time:	09:34:06	**BIC**	-89.195
Sample:	01-01-2008	**HQIC**	-98.544
	- 12-01-2019		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.S.L12	0.0002	1.079	0.000	1.000	-2.115	2.115
ar.S.L24	-0.0003	1.899	-0.000	1.000	-3.722	3.721
ar.S.L36	-0.0002	1.804	-8.78e-05	1.000	-3.536	3.536
ar.S.L48	-0.0004	1.147	-0.000	1.000	-2.248	2.247
ar.S.L60	-0.0004	0.528	-0.001	0.999	-1.036	1.035
ma.S.L12	0.0006	0.253	0.003	0.998	-0.495	0.496
ma.S.L24	0.0001	0.512	0.000	1.000	-1.004	1.004
ma.S.L36	0.0002	0.354	0.000	1.000	-0.693	0.693
ma.S.L48	-1.489e-05	0.067	-0.000	1.000	-0.132	0.132
ma.S.L60	-9.37e-05	0.029	-0.003	0.997	-0.057	0.056
sigma2	1.849e-06	1.24e-06	1.490	0.136	-5.83e-07	4.28e-06

Ljung-Box (L1) (Q):	13.65	**Jarque-Bera (JB):**	2.19
Prob(Q):	0.00	**Prob(JB):**	0.33
Heteroskedasticity (H):	0.16	**Skew:**	-0.65
Prob(H) (two-sided):	0.02	**Kurtosis:**	2.22

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 2.43e+19. Standard errors may be unstable.

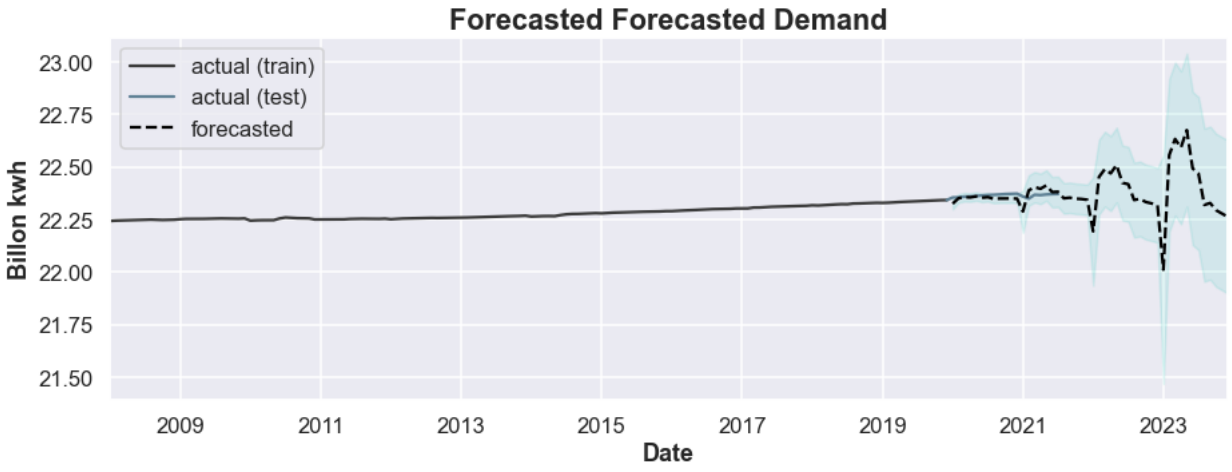
In [95]:
```
SARIMAtr_pred, SARIMAtr_rmse = predict_and_score(SARIMAtr_fit, demand_test)
```

executed in 37ms, finished 09:34:06 2021-10-22

```
The RMSE is 0.029.
```

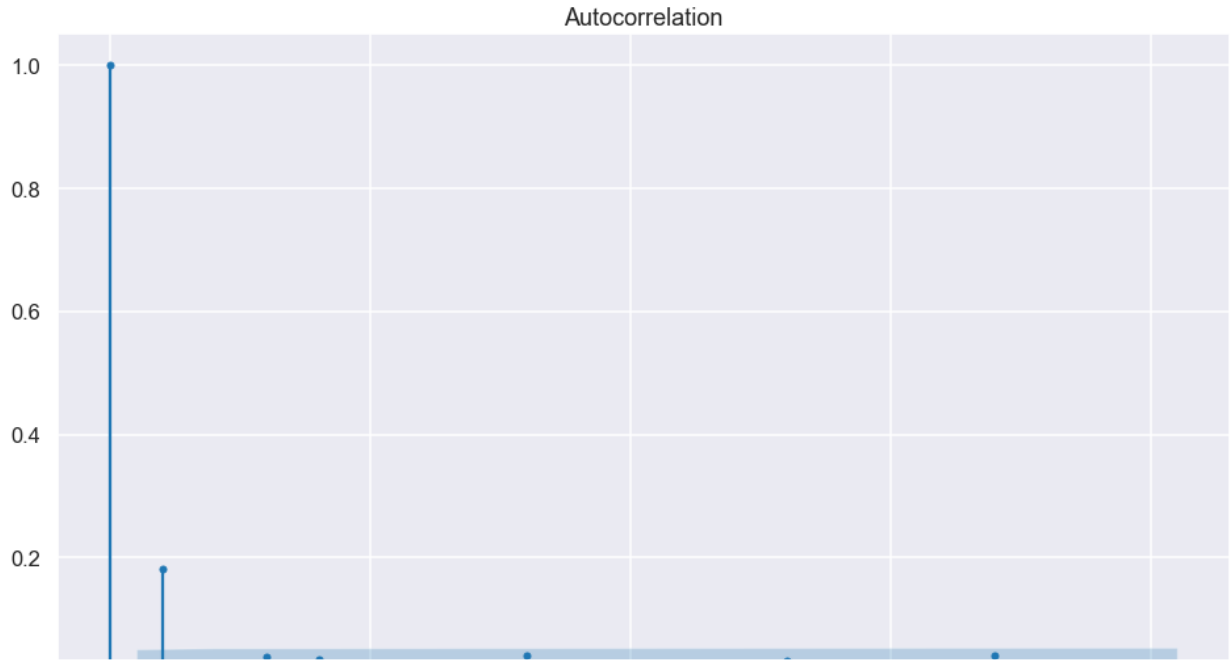
In [96]:
```
SARIMAtr_fcast, SARIMAtr_fcast_plt = plot_forecast(
    demand_train,
    demand_test,
    SARIMAtr_fit,
    48,
    'Forecasted Demand',
    'Billon kwh')
```

executed in 365ms, finished 09:34:06 2021-10-22

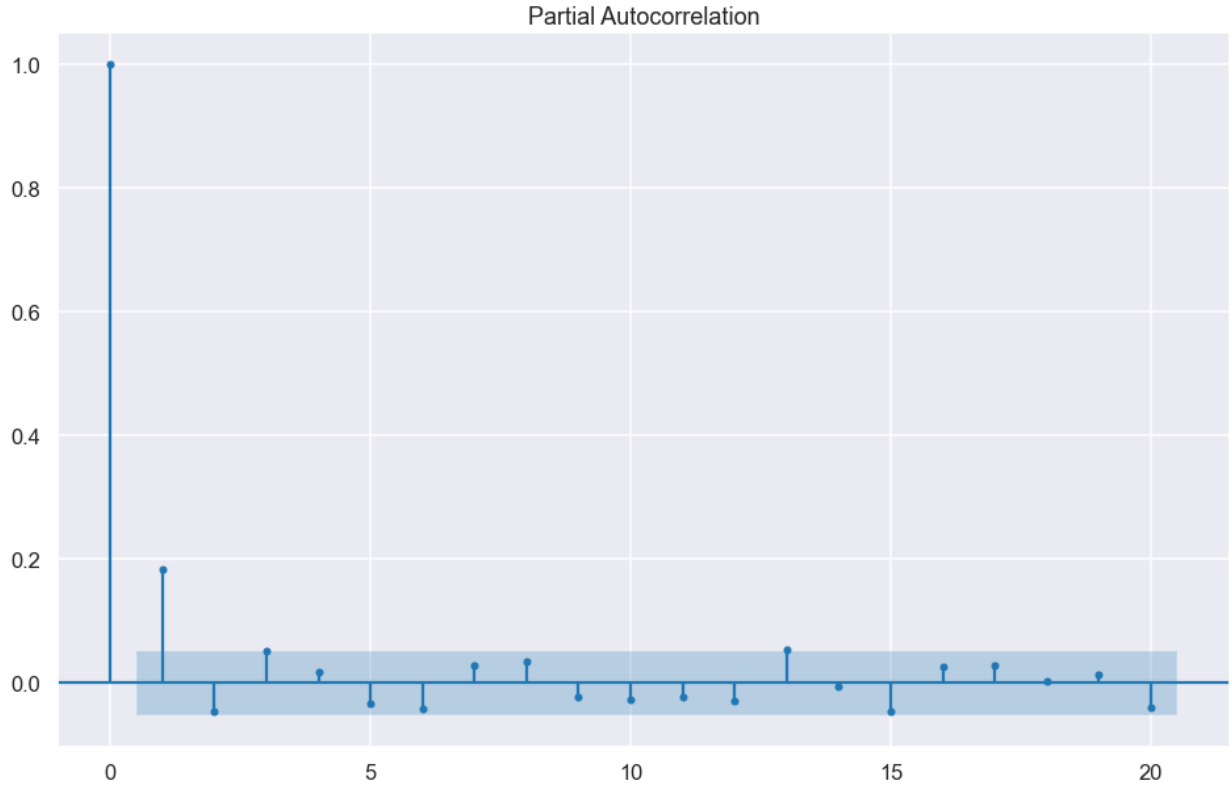


5.3 Mitigate Impact of Rising Natural Gas Prices

In [97]:
```
gas_acf = plot_acf(gas_log, lags=20)
```
executed in 151ms, finished 09:34:07 2021-10-22



In [98]:
```
gas_pacf = plot_pacf(gas_log, lags=20)
```
executed in 154ms, finished 09:34:07 2021-10-22



The plots suggest MA and AR components of 1.

5.3.1 Naive Model

In [204]:
```
#Naive model predicting the mean
gas_naive_pred = [gas_train.mean() for n in range(len(gas_test))]
gas_naive_rmse = round(
    np.sqrt(
        mean_squared_error(
            gas_test,
            gas_naive_pred))
    ,3
)
print(f'The naive RMSE is {gas_naive_rmse}.')
```

executed in 35ms, finished 10:23:36 2021-10-22

```
The naive RMSE is 0.425.
```

5.3.2 Simple ARIMA Model

In [100]:
```
#Model with AR and MA components of 1 and a 1st difference
gas_ARIMA = SARIMAX(
    gas_train,
    order = (1,1,1)
)
gas_ARIMA_fit = gas_ARIMA.fit()
gas_ARIMA_fit.summary()
```

executed in 212ms, finished 09:34:07 2021-10-22

Out[100]:

SARIMAX Results

Dep. Variable:	price	**No. Observations:**	1302
Model:	SARIMAX(1, 1, 1)	**Log Likelihood**	2108.260
Date:	Fri, 22 Oct 2021	**AIC**	-4210.521
Time:	09:34:07	**BIC**	-4195.008
Sample:	01-23-1994	**HQIC**	-4204.701
	- 12-30-2018		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.1204	0.116	-1.042	0.297	-0.347	0.106
ma.L1	0.3184	0.111	2.869	0.004	0.101	0.536
sigma2	0.0023	7.27e-05	31.526	0.000	0.002	0.002

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	72.88
Prob(Q):	1.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.62	**Skew:**	-0.10
Prob(H) (two-sided):	0.00	**Kurtosis:**	4.14

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [101]:
```
gas_ARIMA_pred, gas_ARIMA_rmse = predict_and_score(gas_ARIMA_fit, gas_test)
```

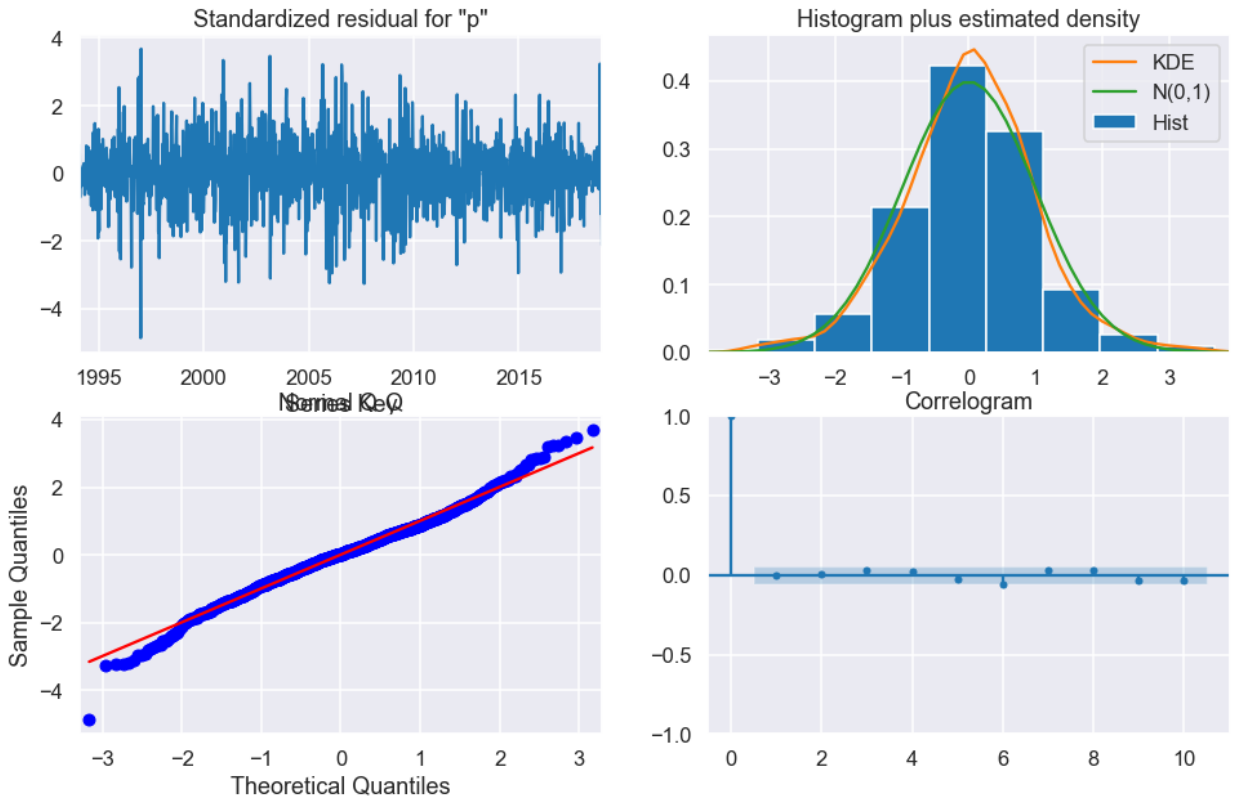
executed in 50ms, finished 09:34:07 2021-10-22

```
The RMSE is 0.312.
```

In [102]:
```
gas_ARIMA_diagnostic = diagnostic_plot(gas_ARIMA_fit)
```

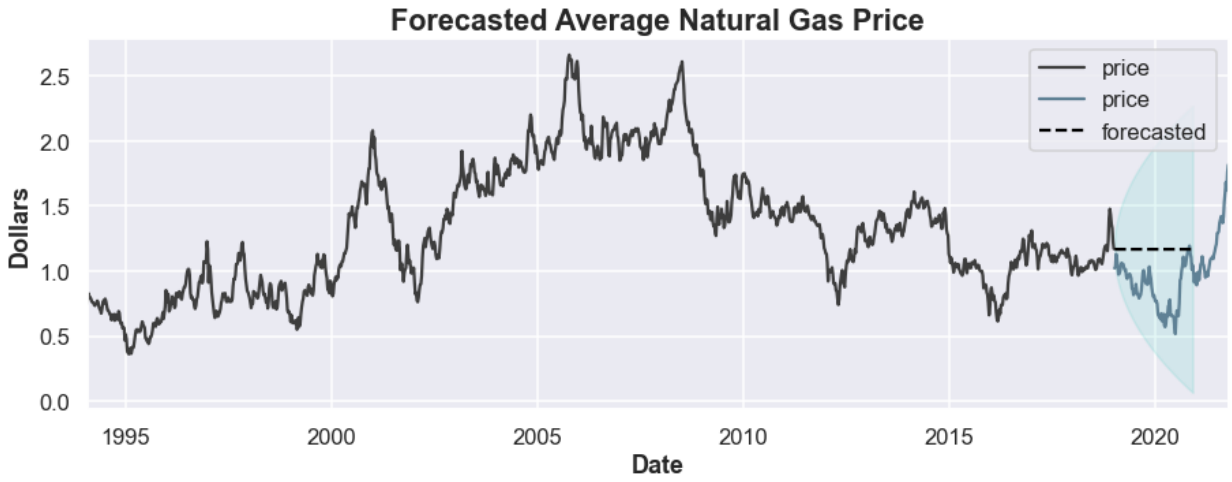
executed in 681ms, finished 09:34:08 2021-10-22

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/gra
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)

<Figure size 1152x720 with 0 Axes>
```



In [103]:
```
gas_ARIMA_fcast, gas_ARIMA_fcast_plt = plot_forecast(
    gas_train,
    gas_test,
    gas_ARIMA_fit,
    100,
    'Average Natural Gas Price',
    'Dollars')
```

executed in 334ms, finished 09:34:08 2021-10-22



Although the diagnostics look good, the RMSE is slightly smaller than the naive model.

5.3.3 SARIMA Model

In [104]:
```
#Run grid search to find hyperparameters if file is not in directory
if 'gas_params.joblib' in os.listdir('files'):
    gas_params = joblib.load('files/gas_params.joblib')
else:
    gas_params = grid_search(gas_train, 2, 52)
    joblib.dump(gas_params, 'files/gas_params.joblib')
```

executed in 4ms, finished 09:34:08 2021-10-22

In [105]:
```
#Fit the model with the hyperparameters
gas_SARIMA_fit = get_fit(gas_params, gas_train)
gas_SARIMA_fit.summary()
```

executed in 2m 25s, finished 09:36:33 2021-10-22

ar.S.L52	-1.1902	0.035	-33.774	0.000	-1.259	-1.121
ar.S.L104	-0.4981	0.025	-19.609	0.000	-0.548	-0.448
ma.S.L52	0.0117	0.047	0.251	0.802	-0.080	0.103
ma.S.L104	-0.7200	0.043	-16.615	0.000	-0.805	-0.635
sigma2	0.1214	0.005	22.907	0.000	0.111	0.132

Ljung-Box (L1) (Q):	1052.14	**Jarque-Bera (JB):**	11.86
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.59	**Skew:**	-0.04
Prob(H) (two-sided):	0.00	**Kurtosis:**	3.50

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [106]:
```
#Score the model
gas_SARIMA_pred, gas_SARIMA_rmse = predict_and_score(gas_SARIMA_fit, gas_te
```

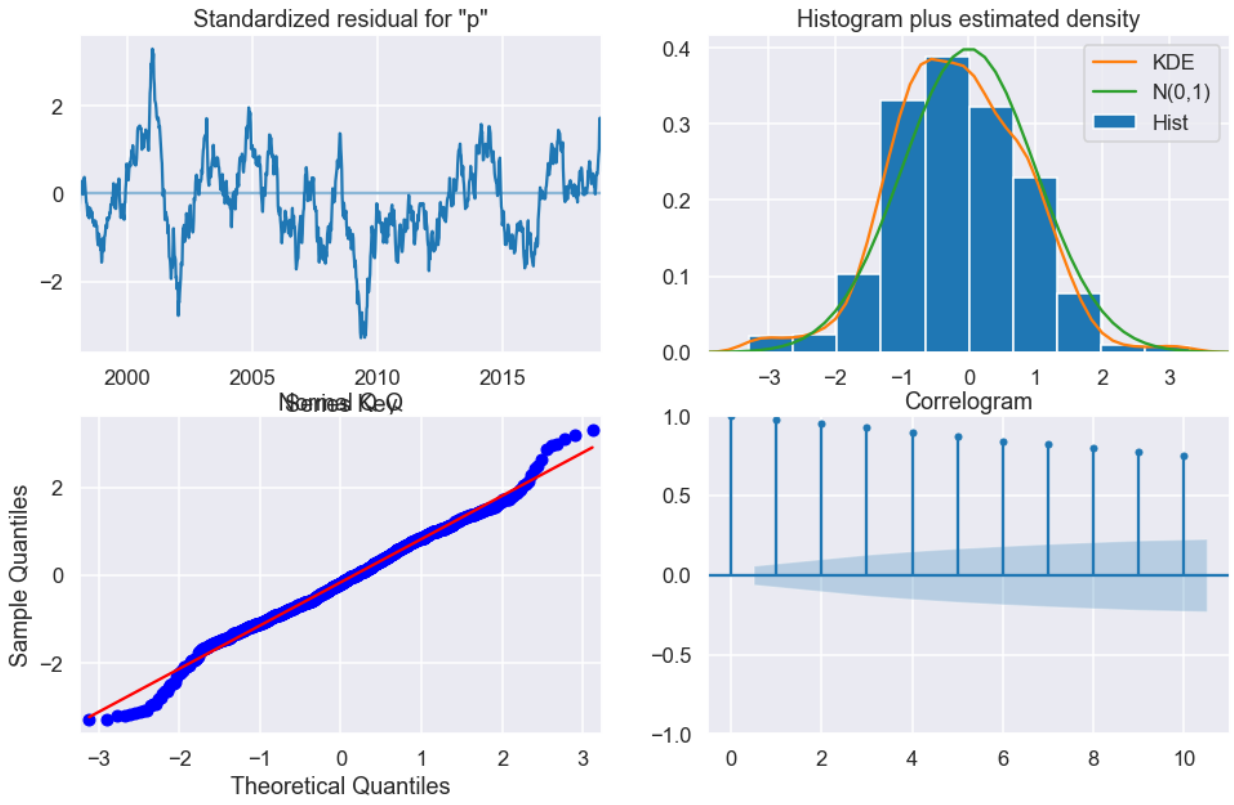
executed in 317ms, finished 09:36:34 2021-10-22

```
The RMSE is 0.291.
```

In [107]:
```
#Plot the diagnostics
gas_SARIMA_diagnostic = diagnostic_plot(gas_SARIMA_fit)
```

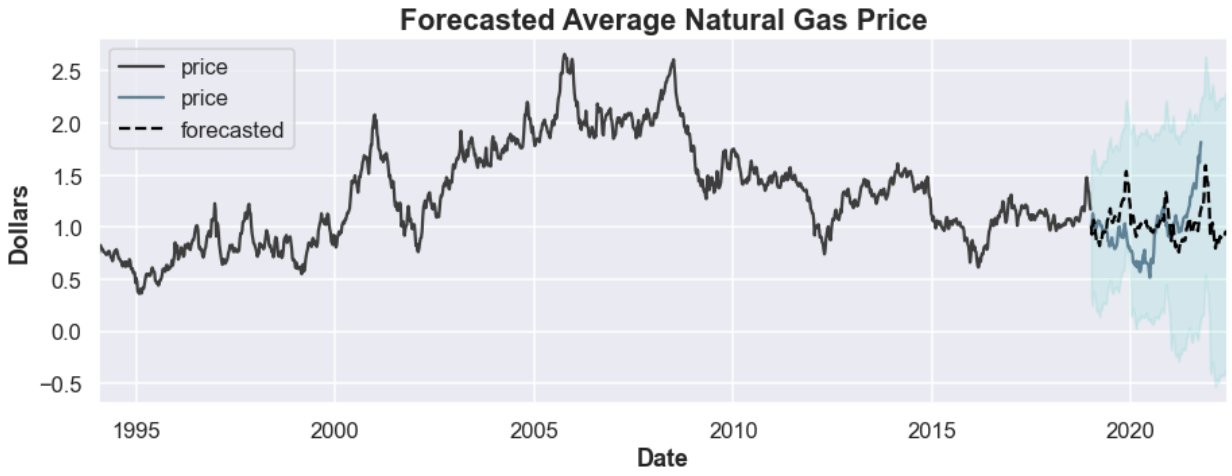
executed in 620ms, finished 09:36:34 2021-10-22

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/gra
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)

<Figure size 1152x720 with 0 Axes>
```



In [108]:
```
#Plot the forecast
gas_SARIMA_fcast, gas_SARIMA_fcast_plt = plot_forecast(
    gas_train,
    gas_test,
    gas_SARIMA_fit,
    180,
    'Average Natural Gas Price',
    'Dollars')
```

executed in 631ms, finished 09:36:35 2021-10-22



The diagnostic plots indicate there is information not being captured by the model and the RMSE is still only slightly better than the naive model.

5.3.4 LSTM

5.3.4.1 Prepare the data, create helper functions and set global variables

In [109]:
```
#Scale and reshape the data
scaler = MinMaxScaler()
scaled_gas = pd.DataFrame(scaler.fit_transform(gas_weekly))

gas_data = scaled_gas.values
gas_data = gas_data.reshape((-1,1))

#Split into train and test sets
split_percent_gas = 0.90
split = int(split_percent_gas*len(gas_data))

gas_train_nn = gas_data[:split]
gas_test_nn = gas_data[split:]

date_train = gas_weekly.index[:split]
date_test = gas_weekly.index[split:]

gas_train_nn.shape, gas_test_nn.shape
```

executed in 15ms, finished 09:36:35 2021-10-22

Out[109]:
```
((1302, 1), (145, 1))
```

In [110]:
```
#Prepare the input data for modeling
LOOK_BACK = 52
N_FEATURES = 1
NUM_EPOCHS = 50

train_generator = TimeseriesGenerator(
    gas_train_nn,
    gas_train_nn,
    length=LOOK_BACK,
    batch_size=20
)
test_generator = TimeseriesGenerator(
    gas_test_nn,
    gas_test_nn,
    length=LOOK_BACK,
    batch_size=1
)
```

executed in 4ms, finished 09:36:35 2021-10-22

In [111]:
```
def eval_and_pred(
    train_generator,
    gas_train_nn,
    test_generator,
    gas_test_nn,
    model):
    """ Takes in the train and test generators, train and test splits and
    the fitted model and returns the mse and a dataframe with the actual an
    predicted values."""

    prediction_test = model.predict(test_generator)
    prediction_train = model.predict(train_generator)
    gas_train_nn = gas_train_nn.reshape((-1))
    gas_test_nn = gas_test_nn.reshape((-1))
    prediction_test = prediction_test.reshape((-1))
    prediction_train = prediction_train.reshape((-1))

    pred_df = pd.DataFrame(index=date_test[LOOK_BACK:])
    pred_df['pred'] = prediction_test
    pred_df['actual'] = gas_test_nn[LOOK_BACK:]

    gas_nn_rmse = np.sqrt(
        mean_squared_error(
            gas_test_nn[LOOK_BACK:],
            prediction_test)
    )

    return gas_nn_rmse, pred_df
```

executed in 5ms, finished 09:36:35 2021-10-22

In [112]:
```
def rolling_predictions(gas_train_nn, gas_test_nn, date_test, model):
    """Takes in the train and test splits, the test dates and the trained
    model and returns a dataframe with the rolling predictions."""
    test_predictions = []

    first_eval_batch = gas_train_nn[-LOOK_BACK:]

    current_batch = first_eval_batch.reshape((1, LOOK_BACK, N_FEATURES))
    for i in range(len(gas_test_nn)):
        pred = model.predict(current_batch)[0]
        test_predictions.append(pred)
        current_batch = np.append(current_batch[:,1:,:],
                                  [[pred]],
                                  axis=1)

    pred_df = pd.DataFrame(index=date_test)
    pred_df['pred'] = pd.DataFrame(test_predictions).values
    pred_df['actual'] = gas_test_nn

    return pred_df
```

executed in 4ms, finished 09:36:35 2021-10-22

5.3.4.2 Model 1

In [113]:
```
#Create an LSTM model with a single bidirectional layer and a single dense
#layer
lstm_model_1 = Sequential()

forward_layer = LSTM(
    10,
    return_sequences=True)

lstm_model_1.add(
    Bidirectional(
        forward_layer,
        input_shape=(LOOK_BACK, N_FEATURES)))

lstm_model_1.add(Flatten())

lstm_model_1.add(Dense(1))

lstm_model_1.compile(optimizer='adam', loss='mse')

lstm_model_1.summary()
```

executed in 753ms, finished 09:36:36 2021-10-22

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional (Bidirectional (None, 52, 20)            960
_________________________________________________________________
flatten (Flatten)            (None, 1040)              0
_________________________________________________________________
dense (Dense)                (None, 1)                 1041
=================================================================
Total params: 2,001
Trainable params: 2,001
Non-trainable params: 0
_________________________________________________________________
```

In [114]:
```
#Fit the model
lstm_model_1.fit_generator(
    train_generator,
    epochs=NUM_EPOCHS,
    verbose=True,
    callbacks=[EarlyStopping(
        monitor='loss',
        patience=5,
        restore_best_weights=True
    )]
)
```

executed in 48.6s, finished 09:37:24 2021-10-22

```
WARNING:tensorflow:From <ipython-input-114-47253c4a2cf8>:2: Model.fit_gen
erator (from tensorflow.python.keras.engine.training) is deprecated and w
ill be removed in a future version.
Instructions for updating:
Please use Model.fit, which supports generators.
Epoch 1/50
63/63 [==============================] - 1s 17ms/step - loss: 0.0082
Epoch 2/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0042
Epoch 3/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0052
Epoch 4/50
63/63 [==============================] - 1s 13ms/step - loss: 0.0044
Epoch 5/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0038
Epoch 6/50
63/63 [==============================] - 1s 16ms/step - loss: 0.0024
Epoch 7/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0029
Epoch 8/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0024
Epoch 9/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0022
Epoch 10/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0022
Epoch 11/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0019
Epoch 12/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0027
Epoch 13/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0019
Epoch 14/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0016
Epoch 15/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0017
Epoch 16/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0016
Epoch 17/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0015
Epoch 18/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0015
Epoch 19/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0027
Epoch 20/50
```

```
63/63 [==============================] - 1s 14ms/step - loss: 0.0015
Epoch 21/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0014
Epoch 22/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0014
Epoch 23/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0012
Epoch 24/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0012
Epoch 25/50
63/63 [==============================] - 1s 16ms/step - loss: 0.0015
Epoch 26/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0017
Epoch 27/50
63/63 [==============================] - 1s 16ms/step - loss: 0.0017
Epoch 28/50
63/63 [==============================] - 1s 15ms/step - loss: 0.0011
Epoch 29/50
63/63 [==============================] - 1s 17ms/step - loss: 9.7467e-04
Epoch 30/50
63/63 [==============================] - 1s 16ms/step - loss: 9.6576e-04
Epoch 31/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0012
Epoch 32/50
63/63 [==============================] - 1s 13ms/step - loss: 0.0011
Epoch 33/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0011
Epoch 34/50
63/63 [==============================] - 1s 15ms/step - loss: 9.5222e-04
Epoch 35/50
63/63 [==============================] - 1s 13ms/step - loss: 0.0011
Epoch 36/50
63/63 [==============================] - 1s 13ms/step - loss: 0.0011
Epoch 37/50
63/63 [==============================] - 1s 13ms/step - loss: 0.0013
Epoch 38/50
63/63 [==============================] - 1s 12ms/step - loss: 9.4401e-04
Epoch 39/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0017
Epoch 40/50
63/63 [==============================] - 1s 13ms/step - loss: 0.0013
Epoch 41/50
63/63 [==============================] - 1s 13ms/step - loss: 8.4359e-04
Epoch 42/50
63/63 [==============================] - 1s 13ms/step - loss: 0.0011
Epoch 43/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0020
Epoch 44/50
63/63 [==============================] - 1s 14ms/step - loss: 8.5613e-04
Epoch 45/50
63/63 [==============================] - 1s 13ms/step - loss: 9.5142e-04
Epoch 46/50
63/63 [==============================] - 1s 13ms/step - loss: 7.4177e-04
Epoch 47/50
63/63 [==============================] - 1s 13ms/step - loss: 8.9420e-04
Epoch 48/50
63/63 [==============================] - 1s 14ms/step - loss: 0.0013
```

```
Epoch 49/50
63/63 [==============================] - 1s 14ms/step - loss: 9.0373e-04
Epoch 50/50
63/63 [==============================] - 1s 13ms/step - loss: 9.2944e-04
```

Out[114]: <tensorflow.python.keras.callbacks.History at 0x7ff9f65012b0>

In [115]:
```
#Get the RMSE and predictions for the model
lstm_model_1_rmse, lstm_model_1_pred = eval_and_pred(
    train_generator,
    gas_train_nn,
    test_generator,
    gas_test_nn,
    lstm_model_1)
lstm_model_1_rmse
```

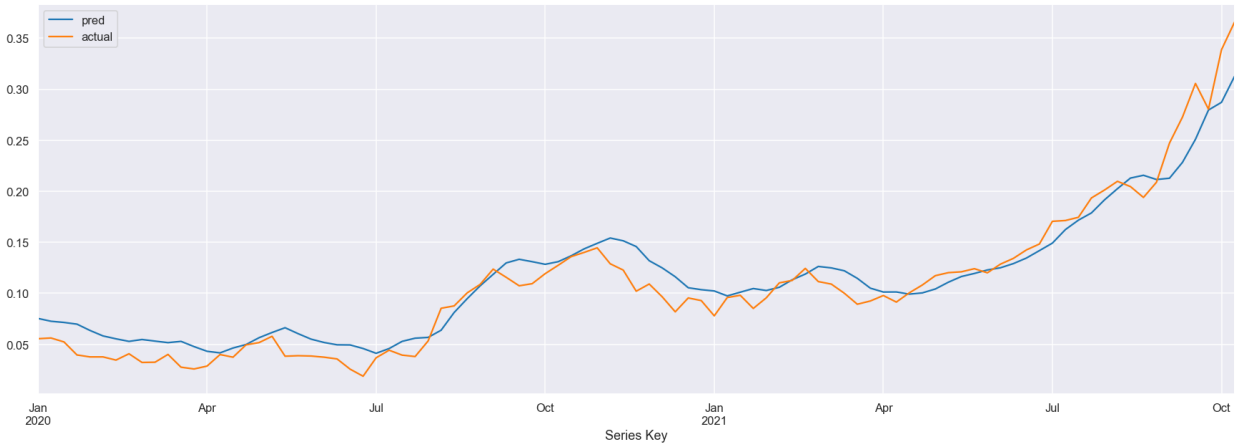
executed in 980ms, finished 09:37:25 2021-10-22

Out[115]: 0.01928537205992838

In [116]:
```
#Plot the predictions
lstm_model_1_pred.plot(figsize=(30,10))
```

executed in 276ms, finished 09:37:26 2021-10-22

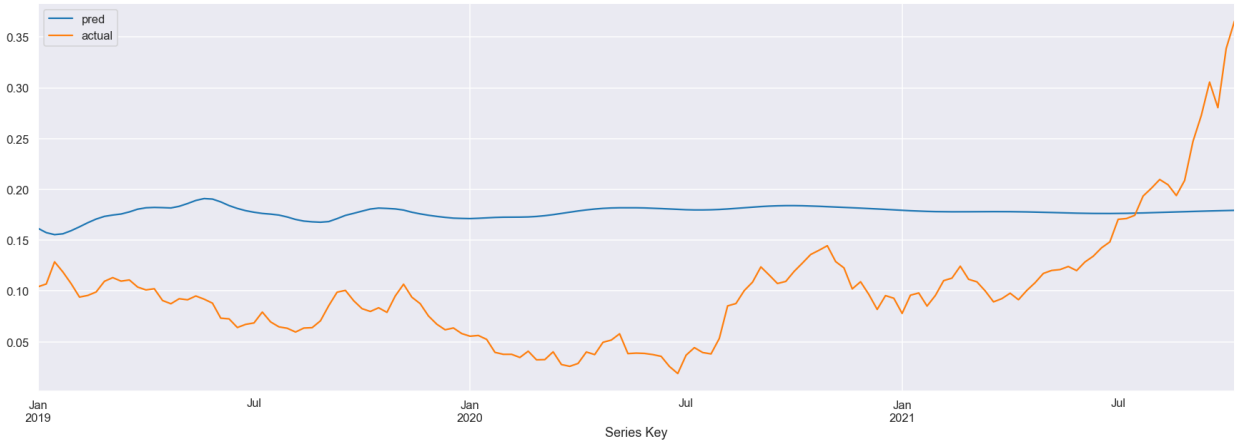
Out[116]: <AxesSubplot:xlabel='Series Key'>



In [117]:
```
#Plot the rolling predictions.
rolling_lstm_model_1 = rolling_predictions(
    gas_train_nn,
    gas_test_nn,
    date_test,
    lstm_model_1)

rolling_lstm_model_1.plot(figsize=(30,10))
```

executed in 4.80s, finished 09:37:31 2021-10-22

Out[117]: <AxesSubplot:xlabel='Series Key'>



5.3.4.3 Model 2

In [118]:
```
#Create an LSTM model with two bidirectional layers and a single dense laye
lstm_model_2 = Sequential()

forward_layer = LSTM(
    10,
    return_sequences=True)

lstm_model_2.add(
    Bidirectional(
        forward_layer,
        input_shape=(LOOK_BACK, N_FEATURES)))

lstm_model_2.add(
    Bidirectional(
        forward_layer,
        input_shape=(LOOK_BACK, N_FEATURES)))

lstm_model_2.add(Flatten())

lstm_model_2.add(Dense(1))

lstm_model_2.compile(optimizer='adam', loss='mse')

lstm_model_2.summary()
```

executed in 829ms, finished 09:37:31 2021-10-22

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional_1 (Bidirection (None, 52, 20)            960
_________________________________________________________________
bidirectional_2 (Bidirection (None, 52, 20)            2480
_________________________________________________________________
flatten_1 (Flatten)          (None, 1040)              0
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 1041
=================================================================
Total params: 4,481
Trainable params: 4,481
Non-trainable params: 0
_________________________________________________________________
```

In [119]:
```
#Fit the model
lstm_model_2.fit_generator(
    train_generator,
    epochs=NUM_EPOCHS,
    verbose=True,
    callbacks=[EarlyStopping(
        monitor='loss',
        patience=5,
        restore_best_weights=True
    )]
)
```

executed in 38.4s, finished 09:38:10 2021-10-22

```
Epoch 10/50
63/63 [==============================] - 2s 34ms/step - loss: 0.0027
Epoch 11/50
63/63 [==============================] - 2s 28ms/step - loss: 0.0032
Epoch 12/50
63/63 [==============================] - 2s 32ms/step - loss: 0.0022
Epoch 13/50
63/63 [==============================] - 2s 30ms/step - loss: 0.0020
Epoch 14/50
63/63 [==============================] - 2s 29ms/step - loss: 0.0024
Epoch 15/50
63/63 [==============================] - 2s 27ms/step - loss: 0.0025
Epoch 16/50
63/63 [==============================] - 2s 29ms/step - loss: 0.0025
Epoch 17/50
63/63 [==============================] - 2s 28ms/step - loss: 0.0023
Epoch 18/50
63/63 [==============================] - 2s 27ms/step - loss: 0.0020
```

Out[119]:
```
<tensorflow.python.keras.callbacks.History at 0x7ffa15fb0520>
```

In [120]:
```
#Get the RMSE and the predictions
lstm_model_2_rmse, lstm_model_2_pred = eval_and_pred(
    train_generator,
    gas_train_nn,
    test_generator,
    gas_test_nn,
    lstm_model_2)
lstm_model_2_rmse
```

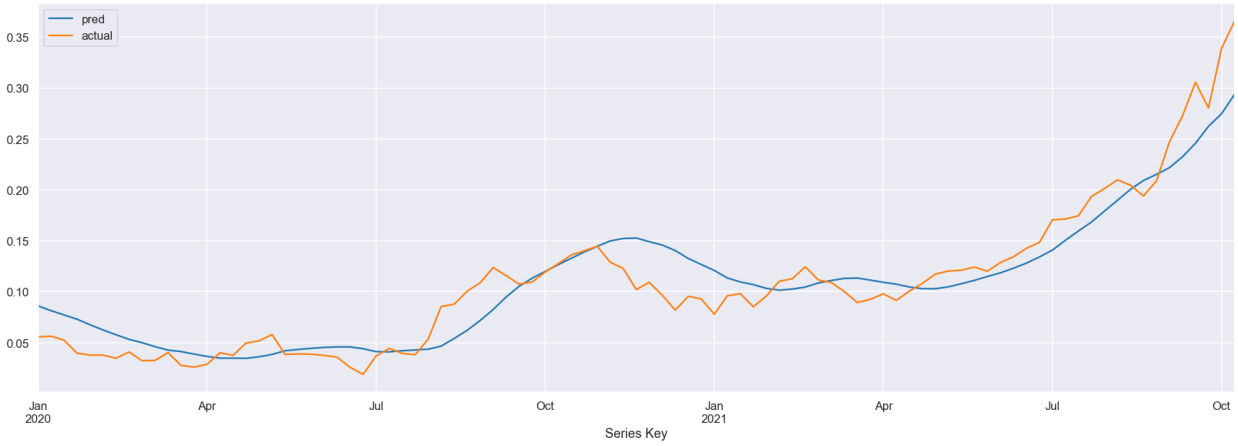
executed in 1.65s, finished 09:38:11 2021-10-22

Out[120]:
```
0.024416447194507123
```

In [121]:
```
#Plot the predictions
lstm_model_2_pred.plot(figsize=(30,10))
```

executed in 280ms, finished 09:38:12 2021-10-22

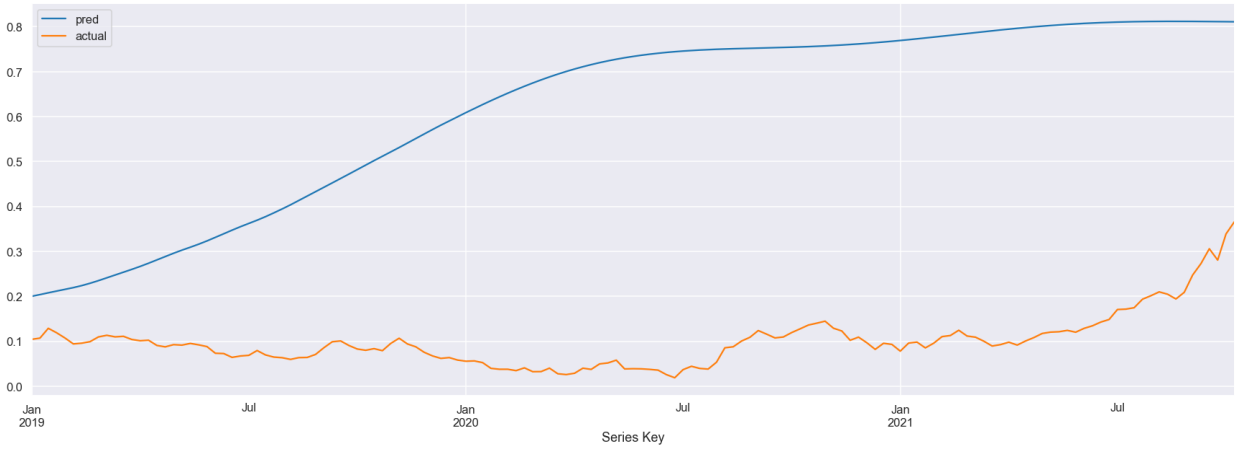
Out[121]: <AxesSubplot:xlabel='Series Key'>



In [122]:
```
#Plot the rolling predictions
rolling_lstm_model_2 = rolling_predictions(
    gas_train_nn,
    gas_test_nn,
    date_test,
    lstm_model_2)

rolling_lstm_model_2.plot(figsize=(30,10))
```

executed in 5.56s, finished 09:38:17 2021-10-22

Out[122]: <AxesSubplot:xlabel='Series Key'>



5.3.4.4 Model 3

In [123]:
```
#Create an LSTM model with two bidirectional layers, two dense layers and
#regularization.
lstm_model_3 = Sequential()

forward_layer = LSTM(
    10,
    return_sequences=True)

lstm_model_3.add(
    Bidirectional(
        forward_layer,
        input_shape=(LOOK_BACK, N_FEATURES)))

lstm_model_3.add(
    Bidirectional(
        forward_layer,
        input_shape=(LOOK_BACK, N_FEATURES)))

lstm_model_3.add(Flatten())

lstm_model_3.add(Dense(
    32,
    kernel_regularizer=regularizers.l1_l2(l1=1e-3, l2=1e-2)))

lstm_model_3.add(Dense(1))

lstm_model_3.compile(optimizer='adam', loss='mse')

lstm_model_3.summary()
```

executed in 631ms, finished 09:38:18 2021-10-22

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
bidirectional_3 (Bidirection (None, 52, 20)            960
_________________________________________________________________
bidirectional_4 (Bidirection (None, 52, 20)            2480
_________________________________________________________________
flatten_2 (Flatten)          (None, 1040)              0
_________________________________________________________________
dense_2 (Dense)              (None, 32)                33312
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 33
=================================================================
Total params: 36,785
Trainable params: 36,785
Non-trainable params: 0
_________________________________________________________________
```

In [124]:
```
#Fit the model
lstm_model_3.fit_generator(
    train_generator,
    epochs=NUM_EPOCHS,
    verbose=True,
    callbacks=[EarlyStopping(
        monitor='loss',
        patience=5,
        restore_best_weights=True
    )]
)
```

executed in 53.2s, finished 09:39:11 2021-10-22

```
Epoch 1/50
63/63 [==============================] - 2s 31ms/step - loss: 0.9187
Epoch 2/50
63/63 [==============================] - 2s 26ms/step - loss: 0.1537
Epoch 3/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0423
Epoch 4/50
63/63 [==============================] - 2s 26ms/step - loss: 0.0246
Epoch 5/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0346
Epoch 6/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0361
Epoch 7/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0210
Epoch 8/50
63/63 [==============================] - 1s 24ms/step - loss: 0.0185
Epoch 9/50
63/63 [==============================] - 2s 24ms/step - loss: 0.0250
Epoch 10/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0186
Epoch 11/50
63/63 [==============================] - 2s 24ms/step - loss: 0.0162
Epoch 12/50
63/63 [==============================] - 2s 24ms/step - loss: 0.0211
Epoch 13/50
63/63 [==============================] - 1s 24ms/step - loss: 0.0139
Epoch 14/50
63/63 [==============================] - 2s 27ms/step - loss: 0.0168
Epoch 15/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0199
Epoch 16/50
63/63 [==============================] - 2s 24ms/step - loss: 0.0177
Epoch 17/50
63/63 [==============================] - 1s 24ms/step - loss: 0.0175
Epoch 18/50
63/63 [==============================] - 1s 24ms/step - loss: 0.0136
Epoch 19/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0161
Epoch 20/50
63/63 [==============================] - 2s 26ms/step - loss: 0.0175
Epoch 21/50
63/63 [==============================] - 2s 30ms/step - loss: 0.0134
Epoch 22/50
```

```
63/63 [==============================] - 2s 30ms/step - loss: 0.0179
Epoch 23/50
63/63 [==============================] - 2s 30ms/step - loss: 0.0161
Epoch 24/50
63/63 [==============================] - 2s 33ms/step - loss: 0.0120
Epoch 25/50
63/63 [==============================] - 2s 33ms/step - loss: 0.0160
Epoch 26/50
63/63 [==============================] - 2s 35ms/step - loss: 0.0176
Epoch 27/50
63/63 [==============================] - 2s 25ms/step - loss: 0.0170
Epoch 28/50
63/63 [==============================] - 2s 24ms/step - loss: 0.0181
Epoch 29/50
63/63 [==============================] - 1s 23ms/step - loss: 0.0126
```

Out[124]:
```
<tensorflow.python.keras.callbacks.History at 0x7ffa74c149d0>
```

In [125]:
```
#Get the RMSE and the predictions
lstm_model_3_rmse, lstm_model_3_pred = eval_and_pred(
    train_generator,
    gas_train_nn,
    test_generator,
    gas_test_nn,
    lstm_model_3)
lstm_model_3_rmse
```

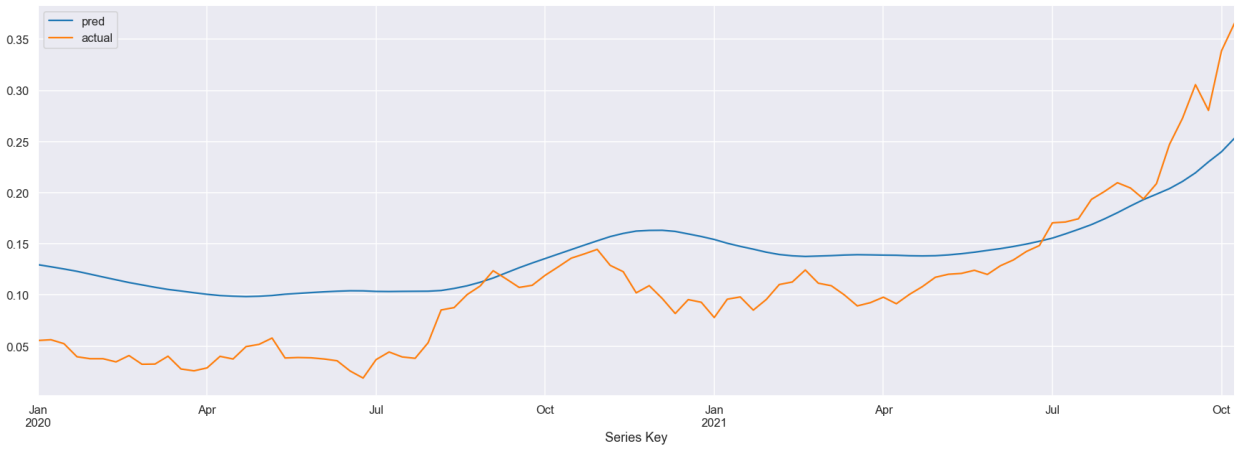
executed in 1.65s, finished 09:39:13 2021-10-22

Out[125]:
```
0.05225734710203399
```

In [126]:
```
#Plot the predictions
lstm_model_3_pred.plot(figsize=(30,10))
```

executed in 272ms, finished 09:39:13 2021-10-22

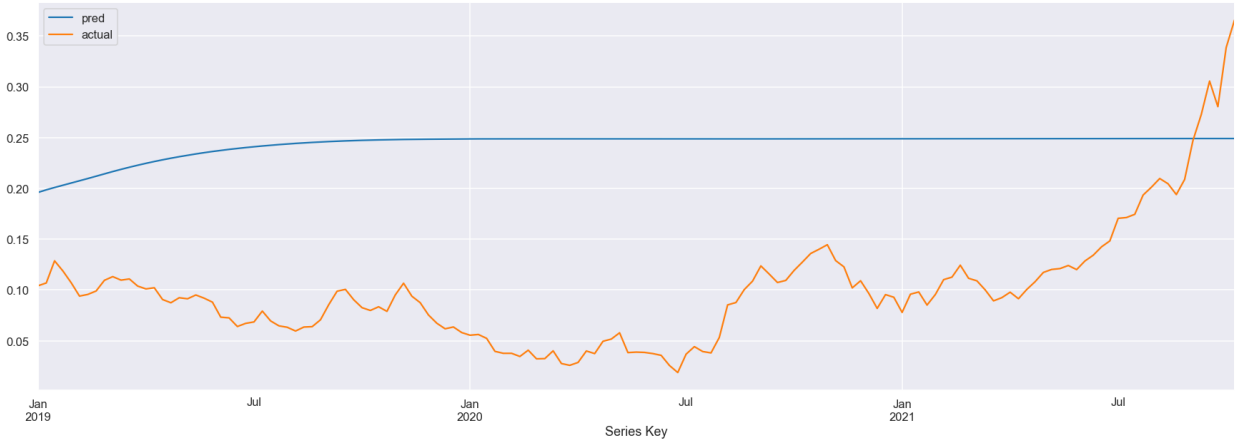
Out[126]:
```
<AxesSubplot:xlabel='Series Key'>
```



In [127]:
```
#Plot the rolling predictions
rolling_lstm_model_3 = rolling_predictions(
    gas_train_nn,
    gas_test_nn,
    date_test,
    lstm_model_3)

rolling_lstm_model_3.plot(figsize=(30,10))
```

executed in 5.62s, finished 09:39:19 2021-10-22

Out[127]: <AxesSubplot:xlabel='Series Key'>



In [128]:
```
#RMSE for rolling predictions
np.sqrt(
    mean_squared_error(
        rolling_lstm_model_3['actual'], rolling_lstm_model_3['pred']))
```

executed in 4ms, finished 09:39:19 2021-10-22

Out[128]: 0.15551591377144755

Model 3 has the best RMSE and is generalizing relatively well.

In [129]:
```
#Train model 3 on the entire data set
data_generator = TimeseriesGenerator(
    gas_data,
    gas_data,
    length=LOOK_BACK,
    batch_size=20
)

lstm_model_3.fit_generator(
    data_generator,
    epochs=NUM_EPOCHS,
    verbose=True,
    callbacks=[EarlyStopping(
        monitor='loss',
        patience=5,
        restore_best_weights=True
    )]
)
```

executed in 13.3s, finished 09:39:32 2021-10-22

```
Epoch 1/50
70/70 [==============================] - 2s 25ms/step - loss: 0.0128
Epoch 2/50
70/70 [==============================] - 2s 25ms/step - loss: 0.0122
Epoch 3/50
70/70 [==============================] - 2s 25ms/step - loss: 0.0133
Epoch 4/50
70/70 [==============================] - 2s 25ms/step - loss: 0.0134
Epoch 5/50
70/70 [==============================] - 2s 27ms/step - loss: 0.0163
Epoch 6/50
70/70 [==============================] - 2s 28ms/step - loss: 0.0257
Epoch 7/50
70/70 [==============================] - 2s 30ms/step - loss: 0.0269
```

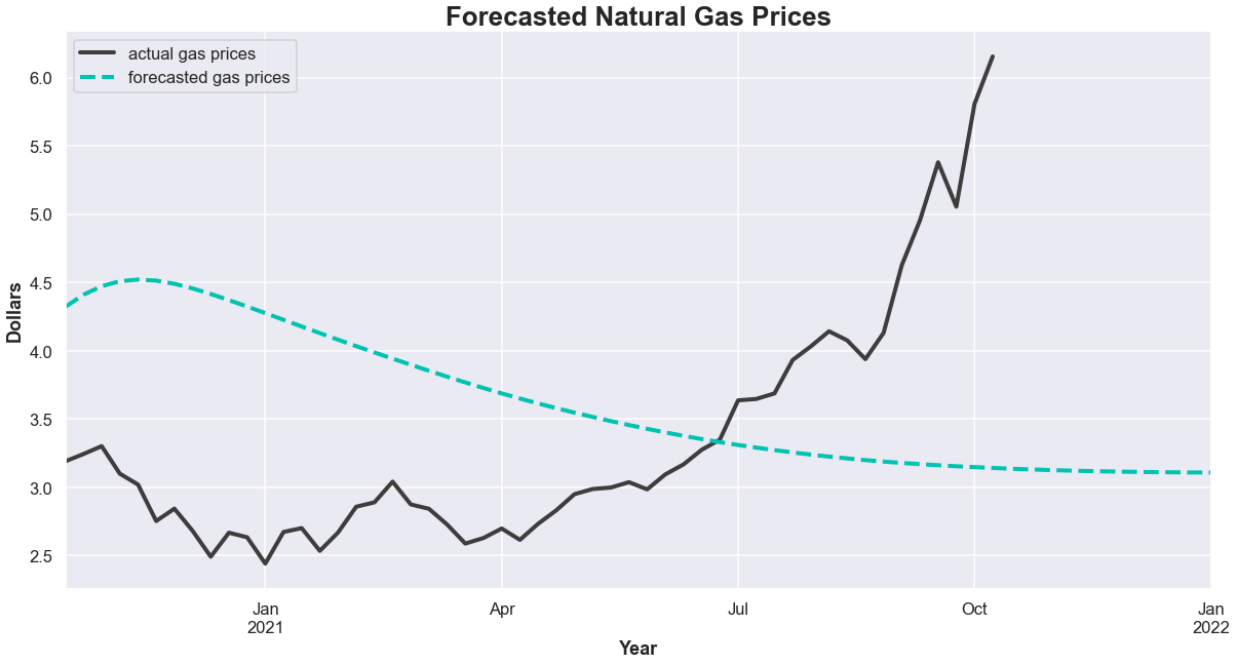
Out[129]:
```
<tensorflow.python.keras.callbacks.History at 0x7ffa15f5d910>
```

In [130]:
```
#Get future predictions
future_dates = pd.date_range(
    start = '2021-10-17',
    freq='W', periods=12
)
all_dates = pd.date_range(
    start = date_test[-LOOK_BACK],
    end = future_dates[-1],
    freq = 'W'
)

test_predictions = []

first_eval_batch = gas_test_nn[-LOOK_BACK:]

current_batch = first_eval_batch.reshape((1, LOOK_BACK, N_FEATURES))
for i in range(len(all_dates)):
    pred = lstm_model_3.predict(current_batch)[0]
    test_predictions.append(pred)
    current_batch = np.append(current_batch[:,1:,:],
                              [[pred]],
                              axis=1)
#Create dataframe with previous 52 weeks of actual and predicted data and 1
#weeks of predicted data
future_df = pd.DataFrame(index=all_dates)
future_df['pred'] = pd.DataFrame(
    scaler.inverse_transform(test_predictions)).values

future_pred = pd.concat([gas_weekly[-LOOK_BACK:], future_df], axis=1)
```

executed in 2.23s, finished 09:39:34 2021-10-22

In [131]:
```
#Plot rolling and future predictions

future_pred.columns = ([
    'actual gas prices',
    'forecasted gas prices'
])

fig,ax = plt.subplots(figsize=(20,10))
future_pred['actual gas prices'].plot(
    color=DARK_NEUTRAL,
    linewidth=4
)

future_pred['forecasted gas prices'].plot(
    color=HIGHLIGHT,
    linestyle='--',
    linewidth=4
)
ax.legend()
plt.xlabel('Year', weight='bold')
plt.ylabel('Dollars', weight='bold')
plt.title('Forecasted Natural Gas Prices', weight='bold', size='x-large');
```

executed in 271ms, finished 09:39:34 2021-10-22



5.4 Decrease Strain on Power Grid During High Demand Periods

5.4.1 Helper Functions for Linear Regression Modeling

In [132]:
```
def get_residuals(y_test, y_pred):
    """Takes in the prediced and actual values and returns the residuals."""
    return [list(y_test)[i] - list(y_pred)[i] for i in range(len(y_test))]
```

executed in 3ms, finished 09:39:34 2021-10-22

In [133]:
```
def cross_val_and_eval(model, X_train, y_train):
    """Takes in a model and a train set, runs a 5-fold corss validation and
    returns the r2 and RMSE scores for the train and test sets."""
    results = {}
    scores = cross_validate(
        model,
        X_train,
        y_train,
        cv=5,
        scoring = (
            'r2',
            'neg_mean_squared_error'
        ),
        return_train_score=True
    )
    results['train_r2'] = scores['train_r2'].mean()
    results['test_r2'] = scores['test_r2'].mean()
    results['train_rmse'] = (
        np.sqrt(-1*scores['train_neg_mean_squared_error'].mean())
    )
    results['test_rmse'] = (
        np.sqrt(-1*scores['test_neg_mean_squared_error'].mean())
    )

    return results
```

executed in 4ms, finished 09:39:34 2021-10-22

In [134]:
```
def make_scatter(y_pred_train, y_pred_val, residuals_train, residuals_val):
    """Takes in the predicted y values and lists of the train and test
    residuals. Returns two scatterplots, one of the train residuals and
    one of the test."""

    fig, (ax1,ax2) = plt.subplots(1,2, figsize=(16,8))
    fig.tight_layout()
    ax1.scatter(x=y_pred_train, y=residuals_train, color=NEUTRAL)
    ax1.axhline(0, color=HIGHLIGHT)
    ax1.set_title('Training Residuals')
    ax1.set_xlabel('Predicted')
    ax1.set_ylabel('Residuals')
    ax2.scatter(x=y_pred_val, y=residuals_val, color=NEUTRAL)
    ax2.axhline(0, color=HIGHLIGHT)
    ax2.set_title('Validation Residuals')
    ax2.set_xlabel('Predicted')
    ax2.set_ylabel('Residuals')
    return fig, (ax1,ax2)
```

executed in 4ms, finished 09:39:34 2021-10-22

5.4.2 Create and Validate Model for Above-Average

Temperatures

In [135]:
```
# Naive model with an R2 of 0
dr_above = DummyRegressor()
dummy_model_above = dr_above.fit(X_train_above, y_train_above)
dummy_model_above.score(X_train_above, y_train_above)
```

executed in 7ms, finished 09:39:34 2021-10-22

Out[135]: 0.0

In [136]:
```
# Create a stasmodels OLS model
train_above = pd.concat([X_train_above, y_train_above], axis=1)
above_formula = f"{y_train_above.name} ~ {'+'.join(X_train_above.columns)}"
above_model = ols(formula=above_formula, data=train_above).fit()
above_model.summary()
```

executed in 20ms, finished 09:39:35 2021-10-22

Out[136]:

OLS Regression Results

Dep. Variable:	demand	**R-squared:**	0.678
Model:	OLS	**Adj. R-squared:**	0.678
Method:	Least Squares	**F-statistic:**	1529.
Date:	Fri, 22 Oct 2021	**Prob (F-statistic):**	7.77e-181
Time:	09:39:35	**Log-Likelihood:**	-7214.9
No. Observations:	728	**AIC:**	1.443e+04
Df Residuals:	726	**BIC:**	1.444e+04
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2.757e+04	835.418	32.999	0.000	2.59e+04	2.92e+04
extreme	1123.8738	28.743	39.101	0.000	1067.445	1180.303

Omnibus:	18.148	**Durbin-Watson:**	1.977
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	18.830
Skew:	-0.377	**Prob(JB):**	8.15e-05
Kurtosis:	3.228	**Cond. No.**	134.

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The R2 is 70.0, indicating that 70% of the residential electricity demand can be explained by the number of degrees over average of the outside temperature.

The intercept of 26,540 indicates that on a day with an average temperature of 57.8 degrees, the electricity demand in the Southeast region is 28,110 mwh. The coefficient of 1,157 indicates that for every degree above normal, there is an additional demand on the grid of 1,157 mwh.

The Durbin-Watson score of just under 2 shows no autocorrelation and indicates that the residuals are homoscedastic. There are not enough observations for the JB score to be used. The kurtosis value of just over 3 shows slightly heavier tails than a normal distribution.

In [137]:
```
# Use cross evaluation to check for overfitting
lr = LinearRegression()
cross_val_and_eval(lr, X_train_above, y_train_above)
```

executed in 33ms, finished 09:39:35 2021-10-22

Out[137]:
```
{'train_r2': 0.67806141606542,
 'test_r2': 0.6712041806500657,
 'train_rmse': 4871.684272921851,
 'test_rmse': 4893.127540567616}
```

The R2 scores and the RMSE scores are very close between the train and test folds, indicating that there is not overfitting.

In [138]:
```
#Get the predictions for the train and validation sets
model_above = lr.fit(X_train_above,y_train_above)
pred_train_above = model_above.predict(X_train_above)
pred_val_above = model_above.predict(X_val_above)
```

executed in 7ms, finished 09:39:35 2021-10-22

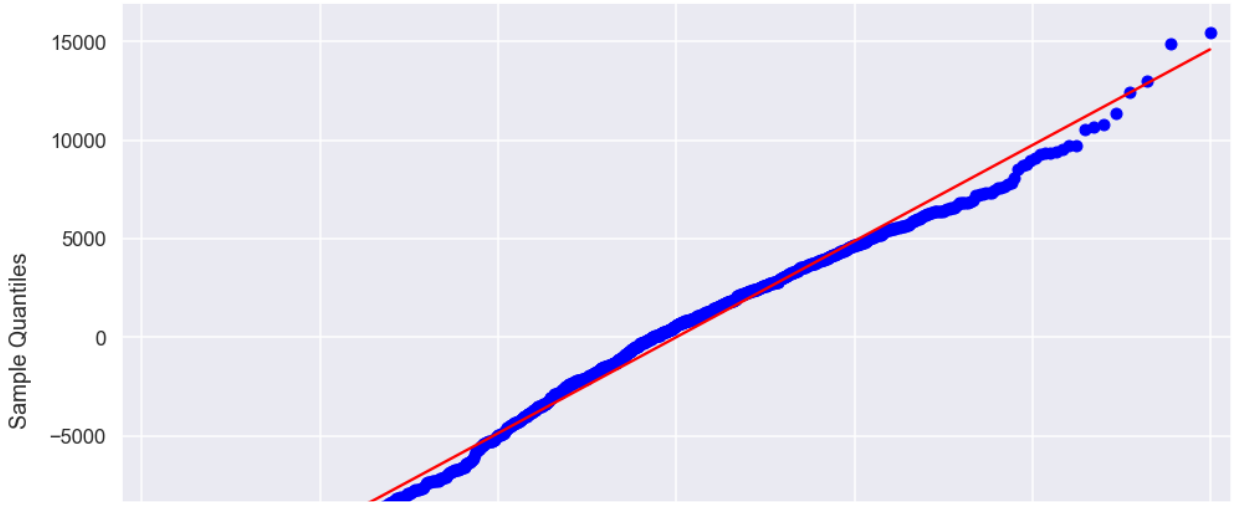
In [139]:
```
#Get the residuals for the train and validation sets
residuals_val = get_residuals(y_val_above, pred_val_above)
residuals_train = get_residuals(y_train_above, pred_train_above)
```

executed in 90ms, finished 09:39:35 2021-10-22

In [140]:
```
#Create the QQ-plot for the training data
train_qq = sm.graphics.qqplot(pd.Series(residuals_train), line='s')
```

executed in 172ms, finished 09:39:35 2021-10-22

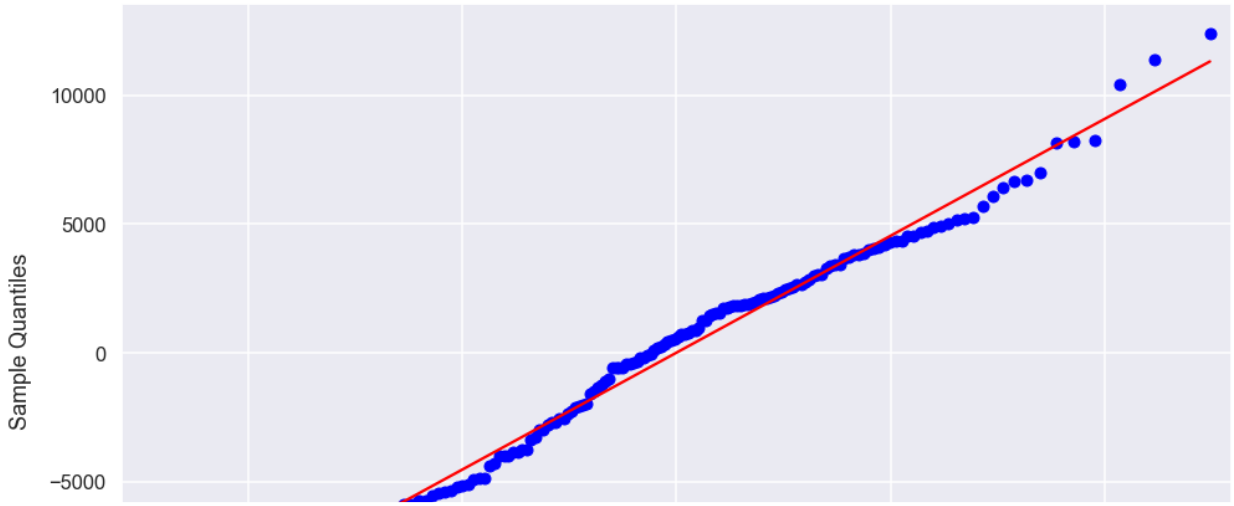
```
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```



In [141]:
```
#Create the QQ-plot for the validation data
val_qq = sm.graphics.qqplot(pd.Series(residuals_val), line='s')
```

executed in 148ms, finished 09:39:35 2021-10-22

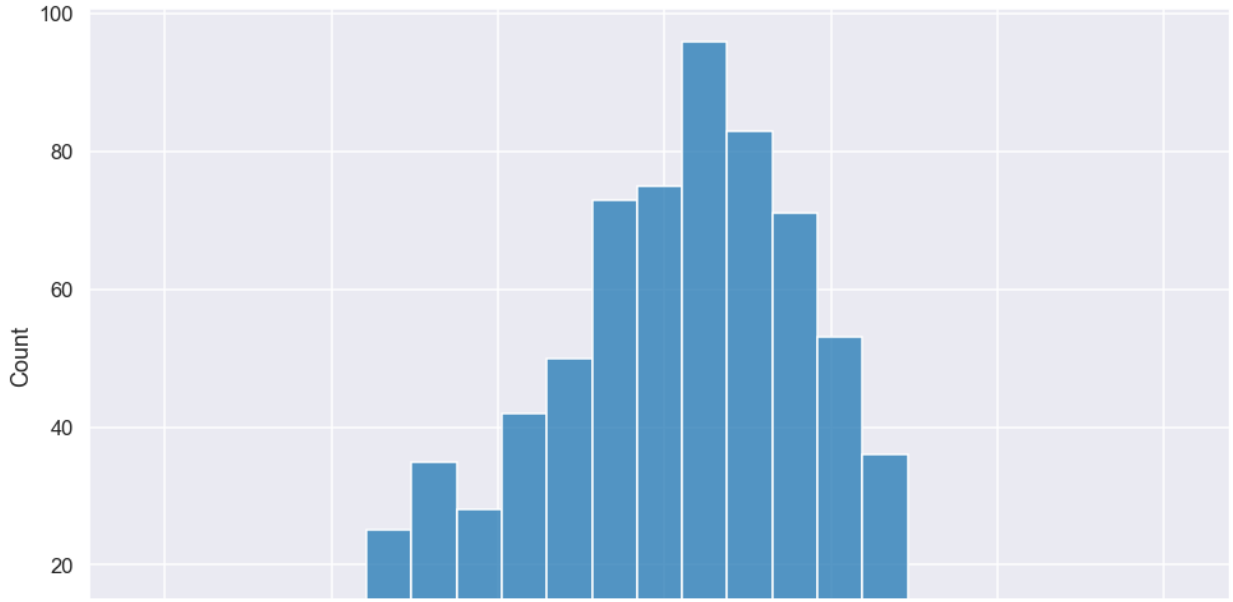
```
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)
```



In [142]:
```
#Plot the histogram for the training data
sns.histplot(residuals_train)
```

executed in 193ms, finished 09:39:35 2021-10-22

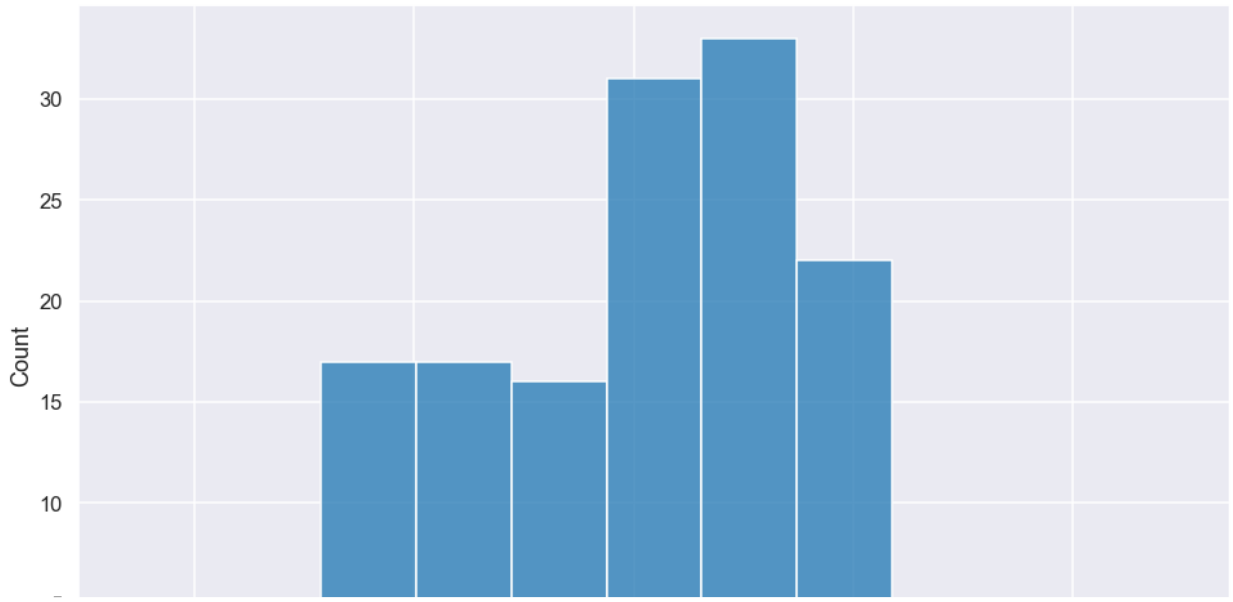
Out[142]: <AxesSubplot:ylabel='Count'>



In [143]:
```
#Plot the histogram for the validation data
sns.histplot(residuals_val)
```

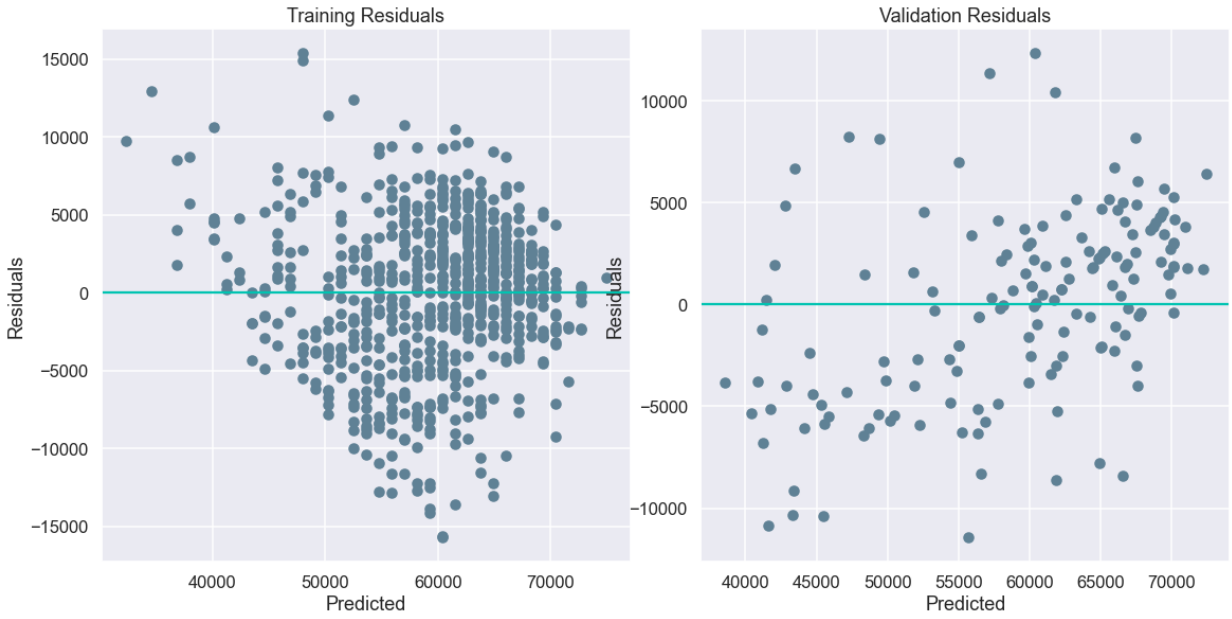
executed in 170ms, finished 09:39:35 2021-10-22

Out[143]: <AxesSubplot:ylabel='Count'>



In [144]:
```
#Plot the scatterplots of the residuals
make_scatter(pred_train_above, y_val_above, residuals_train, residuals_val)
```

executed in 335ms, finished 09:39:36 2021-10-22



Overall, the data meets the requirements for linear regression - there is a linear relationship, the residuals are relatively normally distributed and homoscedastic.

In [145]:
```
#Evaluate on the test data
pred_test_above = model_above.predict(X_test_above)
rmse_test_above = np.sqrt(mean_squared_error(y_test_above, pred_test_above))
model_above_score = model_above.score(X_test_above, y_test_above)
print(rmse_test_above, model_above_score)
```

executed in 7ms, finished 09:39:36 2021-10-22

```
4523.90712748432 0.7211419320200994
```

The results on the test data are consistent with the train and validation data. The RMSE means that on average, the model is off by 4,665 mwh.

5.4.3 Create and Validate Model for Below-Average Temperatures

In [146]:
```
dr_below = DummyRegressor()
dummy_model_below = dr_above.fit(X_train_below, y_train_below)
dummy_model_below.score(X_train_below, y_train_below)
```

executed in 4ms, finished 09:39:36 2021-10-22

Out[146]: 0.0

In [147]:
```
# Create a stasmodels OLS model
train_below = pd.concat([X_train_below, y_train_below], axis=1)
below_formula = f"{y_train_below.name} ~ {'+'.join(X_train_below.columns)}"
below_model = ols(formula=below_formula, data=train_below).fit()
below_model.summary()
```

executed in 18ms, finished 09:39:36 2021-10-22

Covariance Type: nonrobust

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	3.961e+04	329.209	120.330	0.000	3.9e+04	4.03e+04
extreme	-563.0543	19.092	-29.492	0.000	-600.538	-525.571

Omnibus:	66.904	**Durbin-Watson:**	1.902
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	135.675
Skew:	0.576	**Prob(JB):**	3.46e-30
Kurtosis:	4.818	**Cond. No.**	33.0

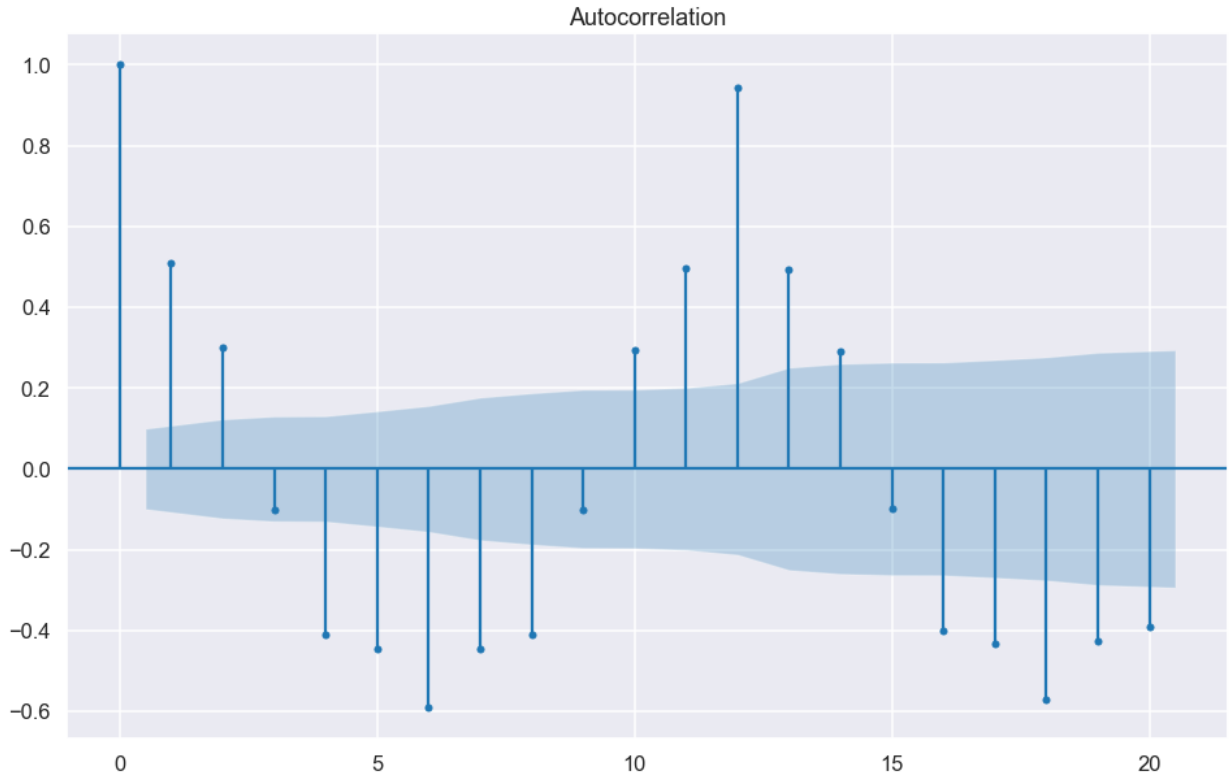
Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

The R2 value of 0.51 indicates that there is not as strong of a relationship between below-average temperatures and electricity demand as there is between above-average temperatures and electricity demand. This makes sense, as around half of the heating of homes in the area comes from natural gas and not electricity (from EIA.gov). Because above-average temperatures are more likely to correlate with high demand and this also corresponds to the peak season for solar power generation, I will focus only on that data.

5.5 Stay Competitive With U.S. Market

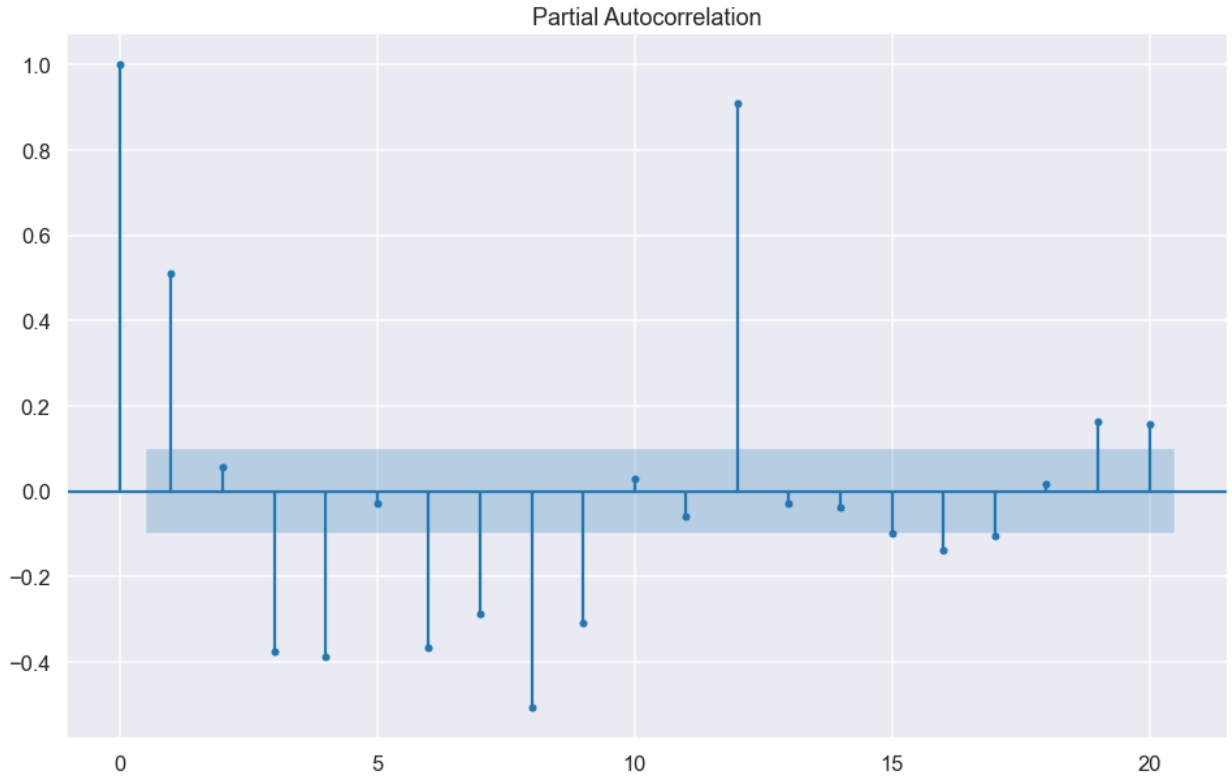
In [148]:
```
#Plot the acf
solar_acf = plot_acf(log_solar.diff().dropna(), lags=20)
```

executed in 154ms, finished 09:39:36 2021-10-22



In [149]:
```
#Plot the pacf
solar_pacf = plot_pacf(log_solar.diff().dropna(), lags=20)
```

executed in 161ms, finished 09:39:36 2021-10-22



The plots suggest an AR of lag 1 and and MA component of lag 2.

5.5.1 Naive Model

In [150]:
```
#Create a naive model that predicts the mean
solar_naive_pred = [solar_train.mean() for n in range(len(solar_test))]
solar_naive_rmse = round(np.sqrt(mean_squared_error(solar_test, solar_naive
print(f'The naive RMSE is {solar_naive_rmse}.')
```

executed in 8ms, finished 09:39:36 2021-10-22

```
The naive RMSE is 4.833.
```

5.5.2 Simple ARIMA Model

In [151]:
```
#Create an ARIMA model with an AR of 1, an MA of 2 and a first difference.
solar_ARIMA = SARIMAX(
    solar_train,
    order = (1,1,2)
)
solar_ARIMA_fit = solar_ARIMA.fit()
solar_ARIMA_fit.summary()
```

executed in 260ms, finished 09:39:36 2021-10-22

Out[151]:

SARIMAX Results

Dep. Variable:	actual	**No. Observations:**	372
Model:	SARIMAX(1, 1, 2)	**Log Likelihood**	303.627
Date:	Fri, 22 Oct 2021	**AIC**	-599.254
Time:	09:39:36	**BIC**	-583.590
Sample:	01-01-1989	**HQIC**	-593.033
	- 12-01-2019		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.2575	0.169	1.523	0.128	-0.074	0.589
ma.L1	0.2108	0.145	1.450	0.147	-0.074	0.496
ma.L2	0.5067	0.094	5.387	0.000	0.322	0.691
sigma2	0.0114	0.001	15.701	0.000	0.010	0.013

Ljung-Box (L1) (Q):	0.04	**Jarque-Bera (JB):**	114.85
Prob(Q):	0.84	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.98	**Skew:**	1.22
Prob(H) (two-sided):	0.92	**Kurtosis:**	4.23

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [152]:
```
#Score the model and get the predictions
solar_ARIMA_pred, solar_ARIMA_rmse = predict_and_score(solar_ARIMA_fit, sol
```

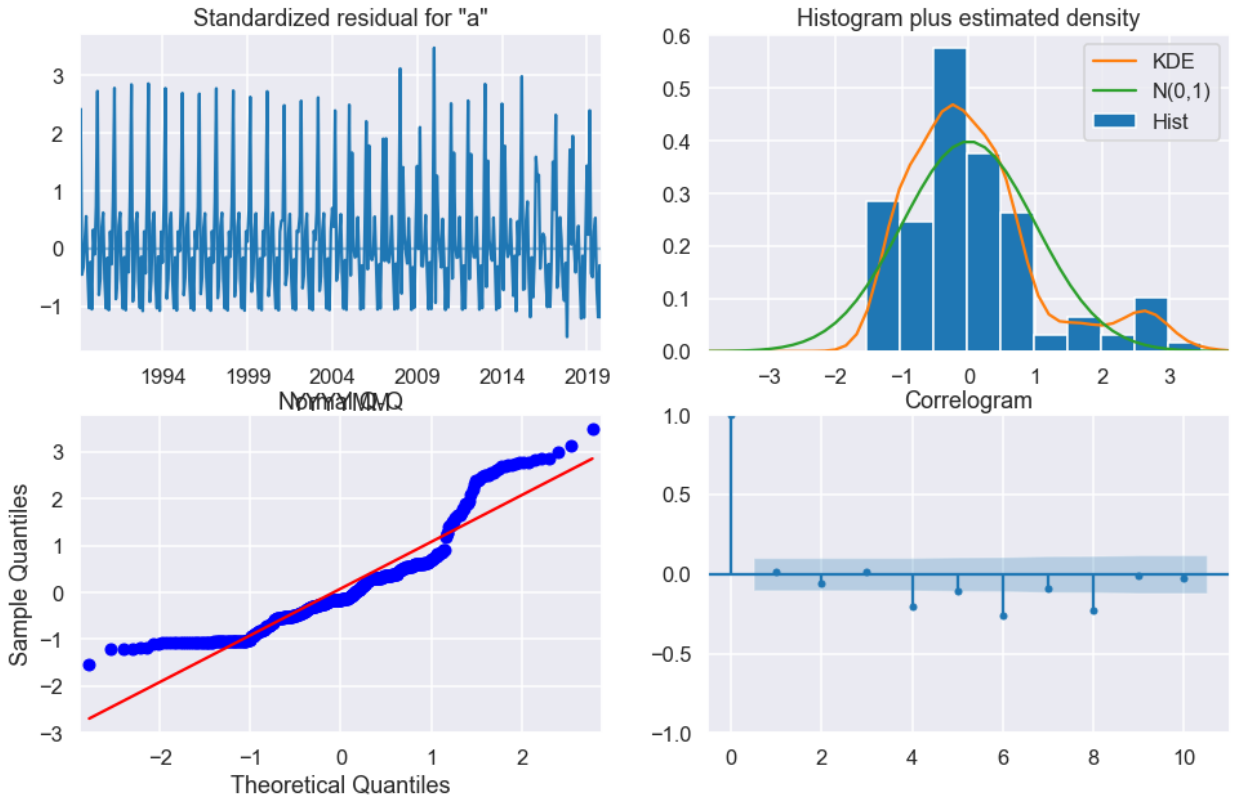
executed in 19ms, finished 09:39:36 2021-10-22

```
The RMSE is 0.738.
```

In [153]:
```
#Get the diagnostics
solar_ARIMA_diagnostic = diagnostic_plot(solar_ARIMA_fit)
```

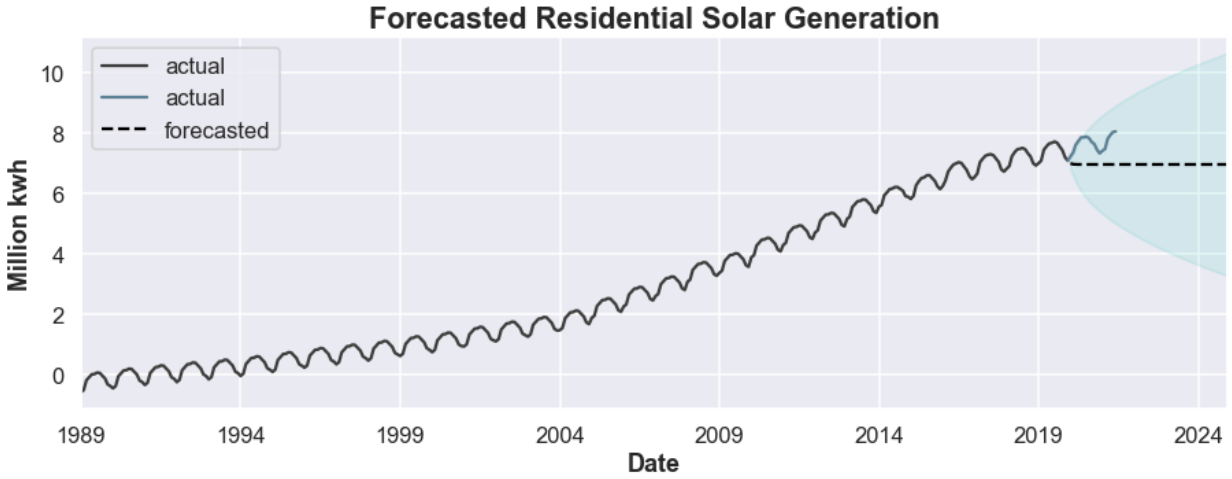
executed in 768ms, finished 09:39:37 2021-10-22

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/gra
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)

<Figure size 1152x720 with 0 Axes>
```



In [154]:
```
#Plot the predictions
solar_ARIMA_fcast, solar_ARIMA_fcast_plt = plot_forecast(
    solar_train,
    solar_test,
    solar_ARIMA_fit,
    60,
    'Residential Solar Generation',
    'Million kwh')
```

executed in 359ms, finished 09:39:37 2021-10-22



Although the RMSE has improved over the naive model, the residuals are far from normal and the model does not capture the data well.

5.5.3 SARIMA Model

In [155]:
```
#Run a grid search for hyperparameters if the file is not already in the
#directory
if 'solar_params.joblib' in os.listdir('files'):
    solar_params = joblib.load('files/solar_params.joblib')
else:
    solar_params = grid_search(solar_train, 2, 12)
    joblib.dump(solar_params, 'files/solar_params.joblib')
```

executed in 6ms, finished 09:39:37 2021-10-22

In [156]:
```
#Fit the model with the hyperparameters
solar_SARIMA_fit = get_fit(solar_params, solar_train)
solar_SARIMA_fit.summary()
```

executed in 3.37s, finished 09:39:41 2021-10-22

ar.S.L12	-0.9447	0.139	-6.786	0.000	-1.218	-0.672
ar.S.L24	-0.7022	0.106	-6.640	0.000	-0.909	-0.495
ma.S.L12	0.4982	0.150	3.311	0.001	0.203	0.793
ma.S.L24	0.5941	0.093	6.385	0.000	0.412	0.776
sigma2	0.0056	0.000	16.391	0.000	0.005	0.006

Ljung-Box (L1) (Q):	235.72	**Jarque-Bera (JB):**	63.94
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	7.47	**Skew:**	0.66
Prob(H) (two-sided):	0.00	**Kurtosis:**	4.74

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [157]:
```
#Score the model and get the predictions
solar_SARIMA_pred, solar_SARIMA_rmse = predict_and_score(solar_SARIMA_fit,
```

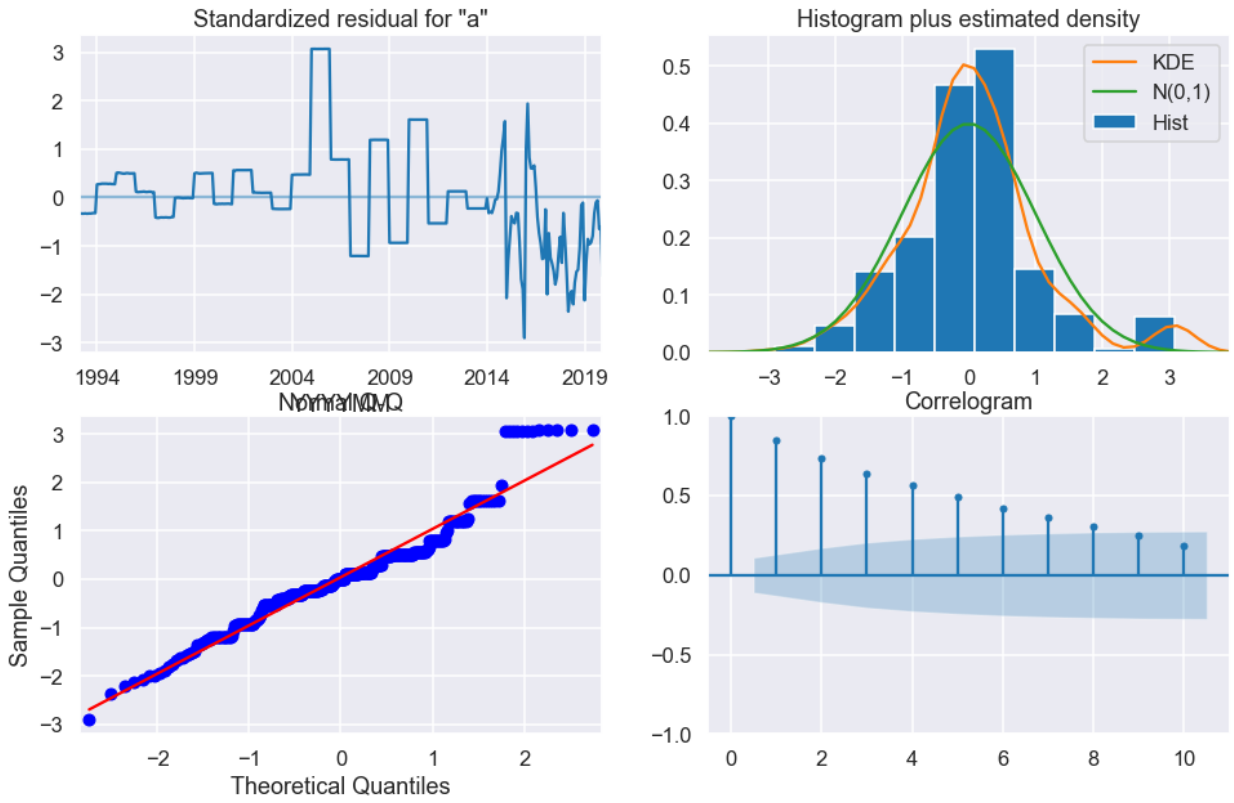
executed in 22ms, finished 09:39:41 2021-10-22

```
The RMSE is 0.123.
```

In [158]:
```
#Plot the diagnostics
solar_SARIMA_diagnostic = diagnostic_plot(solar_SARIMA_fit)
```

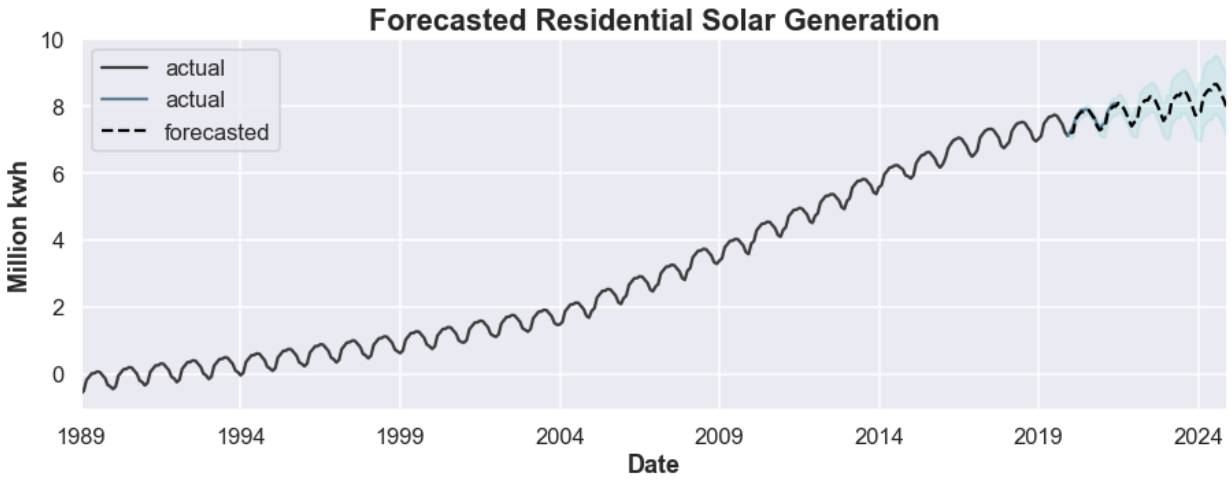
executed in 693ms, finished 09:39:42 2021-10-22

```
/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/statsmodels/gra
phics/gofplots.py:993: UserWarning: marker is redundantly defined by the
'marker' keyword argument and the fmt string "bo" (-> marker='o'). The ke
yword argument will take precedence.
  ax.plot(x, y, fmt, **plot_style)

<Figure size 1152x720 with 0 Axes>
```



In [159]:
```
#Plot the forecast
solar_SARIMA_fcast, solar_SARIMA_fcast_plt = plot_forecast(
    solar_train,
    solar_test,
    solar_SARIMA_fit,
    60,
    'Residential Solar Generation',
    'Million kwh')
```

executed in 361ms, finished 09:39:42 2021-10-22



Although the diagnostics indicate that there are some outliers and that there is information not captured by the model, the RMSE has decreased further and the prediction plot shows that the model is doing an excellent job at predicting the pattern.

The seasonal AR and MA components show that the information from 1 and 2 years ago is predictive of the current value.

6 Data Visualizations

6.1 Reduce Dependence on Imported Electricity

In [160]:
```
pct_change = energy_demand.pct_change(periods=12)
```

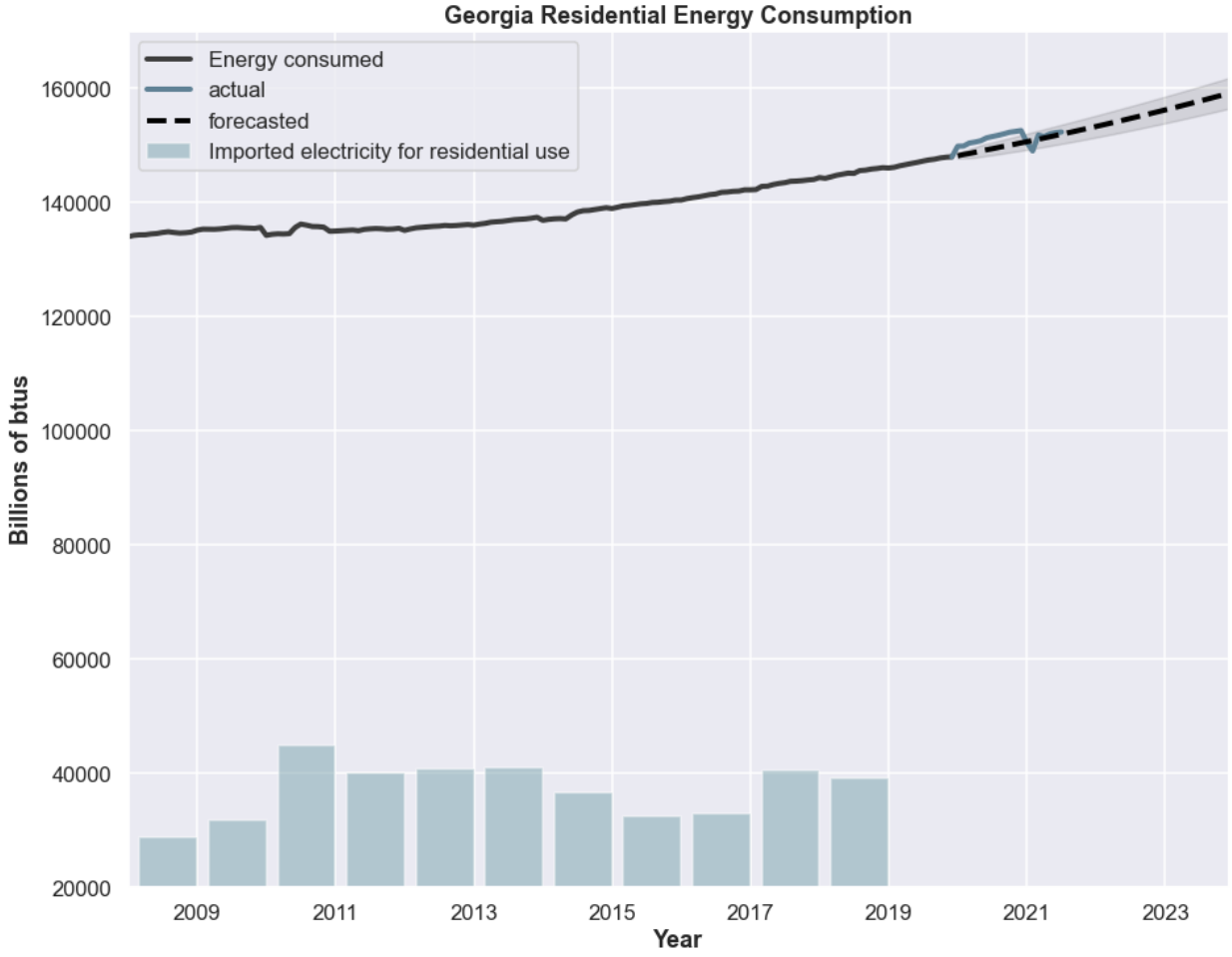
executed in 4ms, finished 09:39:42 2021-10-22

In [161]:
```
#Tranform all data into btus
BTU = 34121
demand_train_btu = np.e**(demand_train)/BTU
demand_test_btu = np.e**(demand_test)/BTU
demand_fcast =np.e**( ARt_fit.get_forecast(
        steps=48,
        dynamic=True).summary_frame())/BTU
by_import = by_source['imported'][:'2008'].sort_index()
```

executed in 14ms, finished 09:39:42 2021-10-22

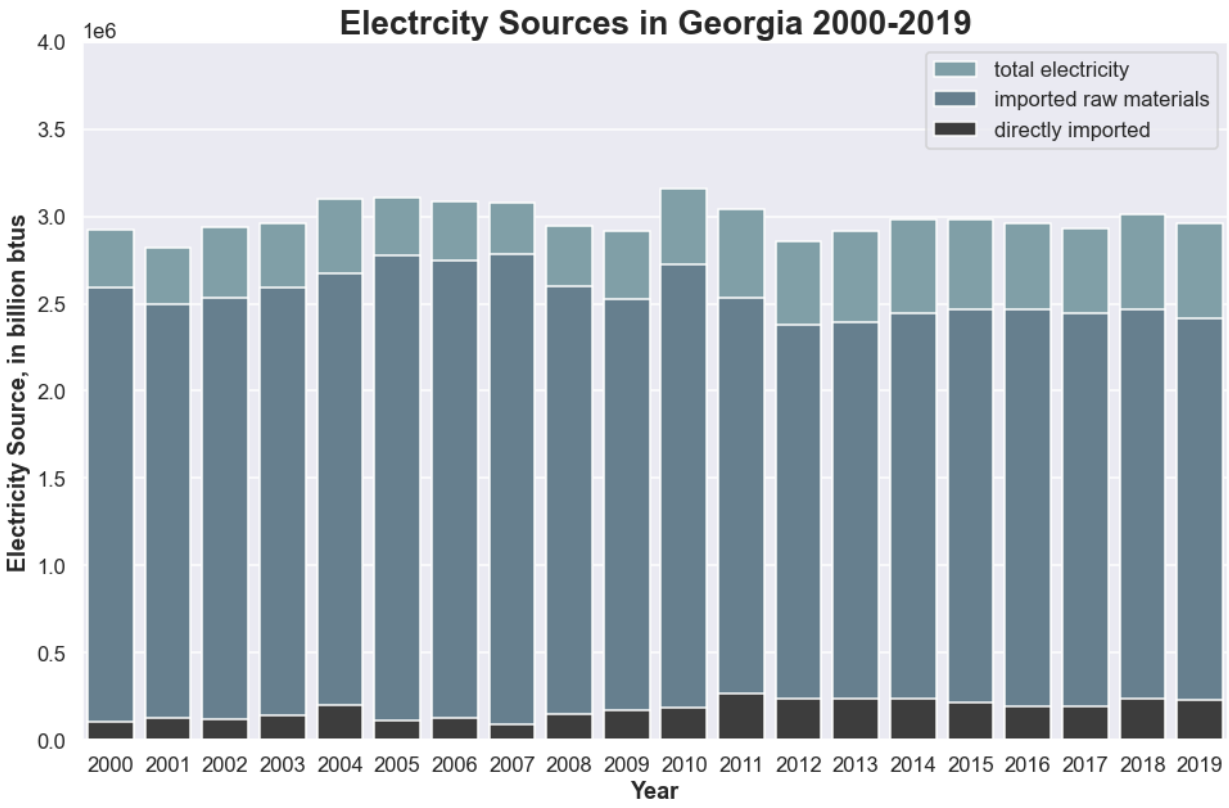
In [162]:
```
#Plot the data
fig, ax = plt.subplots(figsize=(15, 12))

demand_train_btu.plot(
    ax=ax,
    color=DARK_NEUTRAL,
    linewidth=4,
    label='Energy consumed'
    )
demand_test_btu.plot(
    ax=ax,
    color=NEUTRAL,
    linewidth=4,
    label='actual'
    )
demand_fcast['mean'].plot(
    ax=ax,
    style='k--',
    linewidth=4,
    label='forecasted')
ax.fill_between(
    demand_fcast.index,
    demand_fcast['mean_ci_lower'],
    demand_fcast['mean_ci_upper'],
    color='k',
    alpha=0.1)
plt.bar(
    x=by_import.index,
    height=by_import*.17,
    width=-10,
    align='edge',
    color=MEDIUM,
    alpha=.5,
    label = 'Imported electricity for residential use')
plt.xlabel(
    'Year',
    weight='bold'
)
plt.ylabel(
    'Billions of btus',
    weight='bold'
)
plt.title(f'Georgia Residential Energy Consumption', weight='bold')
ax.legend(loc=2)
plt.ylim(20_000, 170_000);
```

executed in 270ms, finished 09:39:42 2021-10-22


Georgia Residential Energy Consumption
Energy consumed
actual
forecasted
Imported electricity for residential use
160000
140000
120000
100000
80000
60000
40000
20000
Billions of btus
2009
2011
2013
2015
2017
2019
2021
2023
Year

In [163]:
```
#Plot the source of electricity by year
by_source['imported_materials'] = (
    by_source['total'] -
    by_source['renewable'] -
    by_source['imported'])

fig,ax = plt.subplots(figsize=(16,10))
sns.barplot(
    data=by_source[:'2000'],
    x=by_source[:'2000'].index.year,
    y='total',
    color=MEDIUM,
    label='total electricity'
)
sns.barplot(
    data=by_source[:'2000'],
    x=by_source[:'2000'].index.year,
    y='imported_materials',
    color=NEUTRAL,
    label='imported raw materials'
)
sns.barplot(
    data=by_source[:'2000'],
    x=by_source[:'2000'].index.year,
    y='imported',
    color=DARK_NEUTRAL,
    label='directly imported'
)
plt.ylim(0, 4_000_000)
plt.legend()
plt.xlabel(
    'Year',
    weight='bold'
)
plt.ylabel(
    'Electricity Source, in billion btus',
    weight='bold'
)
plt.title(
    'Electrcity Sources in Georgia 2000-2019',
    weight='bold',
    size='x-large'
);
```

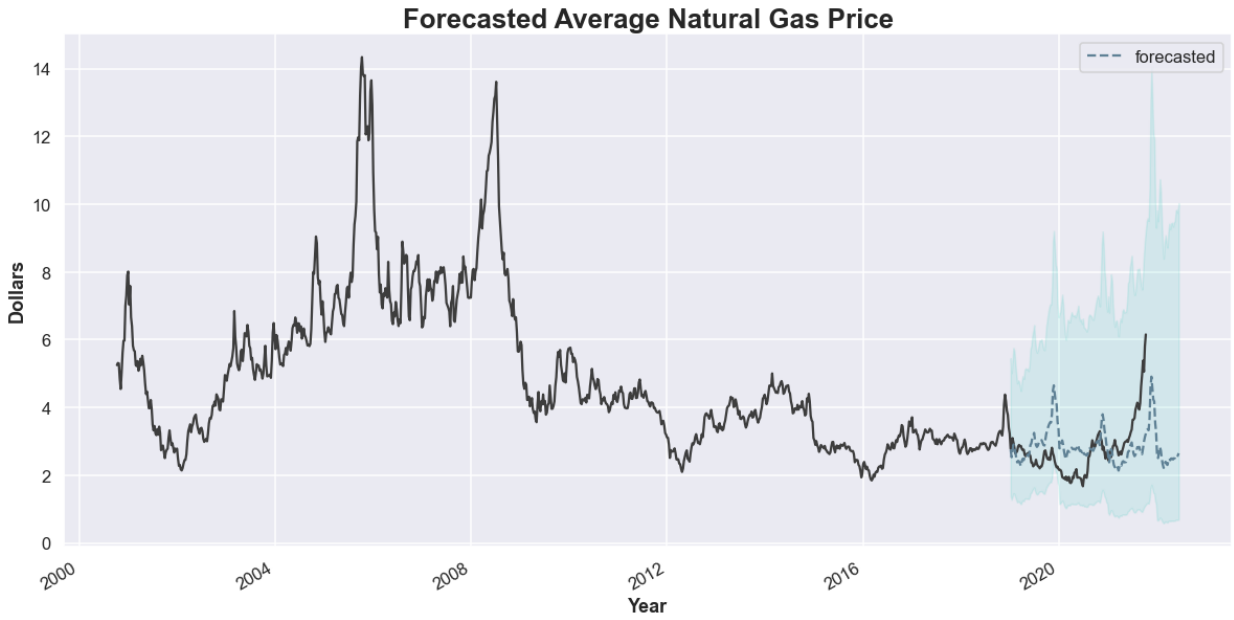
executed in 459ms, finished 09:39:43 2021-10-22



6.2 Mitigate Impact of Rising Natural Gas Prices

In [164]:
```
#Un-log the forecast and plot
fig, ax = plt.subplots(figsize=(20, 10))

sns.lineplot(
    data=gas_weekly[350:],
    x=gas_weekly[350:].index,
    y='price',
    color=DARK_NEUTRAL
)

fcast = np.e**(gas_SARIMA_fit.get_forecast(
    steps=180,
    dynamic=True).summary_frame())

fcast['mean'].plot(
    ax=ax,
    style='--',
    color=NEUTRAL,
    label='forecasted'
)
plt.legend()
ax.fill_between(
    fcast.index,
    fcast['mean_ci_lower'],
    fcast['mean_ci_upper'],
    color=HIGHLIGHT,
    alpha=0.1);
plt.xlabel(
    'Year',
    weight='bold'
)
plt.ylabel(
    'Dollars',
    weight='bold'
)
plt.title(
    'Forecasted Average Natural Gas Price',
    weight='bold',
    size='x-large'
);
```

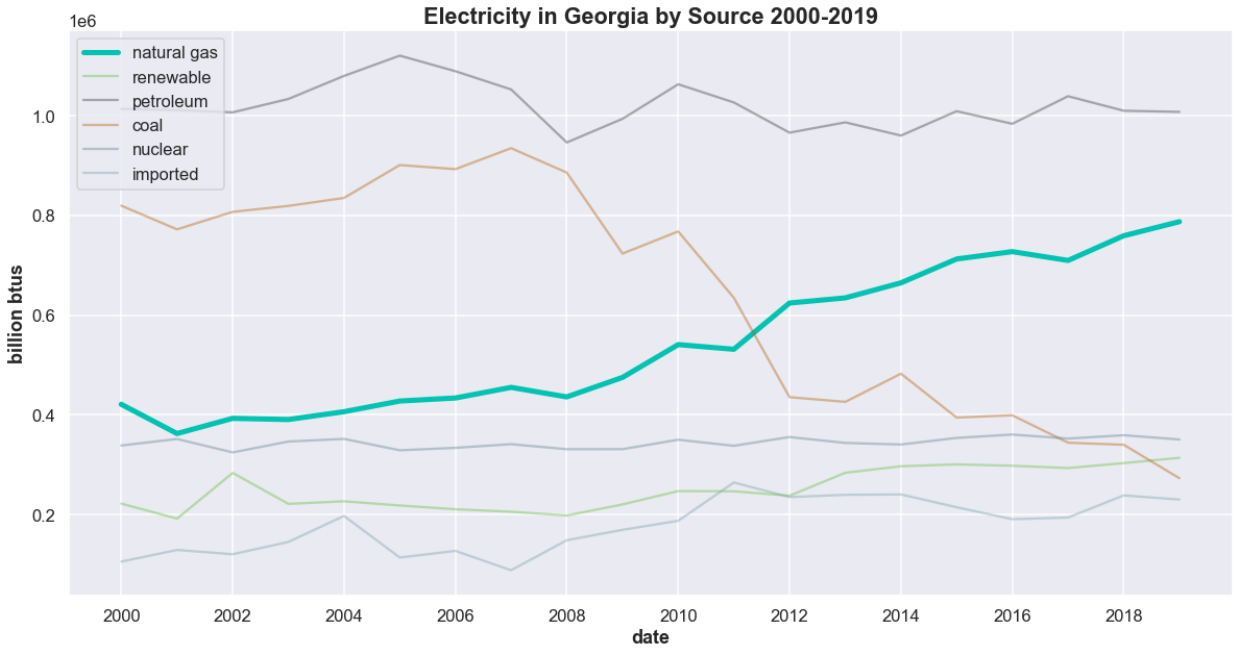
executed in 900ms, finished 09:39:44 2021-10-22


Forecasted Average Natural Gas Price
forecasted
Dollars
Year
0
2
4
6
8
10
12
14
2000
2004
2008
2012
2016
2020

In [165]:
```
#Plot use of natural gas to generate electricity over time
DATA = by_source[:'2000']
IDX = by_source[:'2000'].index
ALPHA = 0.4

fig,ax=plt.subplots(figsize=(20,10))

sns.lineplot(
    data=DATA,
    x=IDX,
    y='natural_gas',
    color=HIGHLIGHT,
    linewidth=5,
    label='natural gas'
)
sns.lineplot(
    data=DATA,
    x=IDX,
    y='renewable',
    color=GREEN,
    alpha=ALPHA,
    label='renewable'
)
sns.lineplot(
    data=DATA,
    x=IDX,
    y='petroleum',
    color=DARK_NEUTRAL,
    alpha=ALPHA,
    label='petroleum'
)
sns.lineplot(
    data=DATA,
    x=IDX,
    y='coal',
    color=BRICK,
    alpha=ALPHA,
    label='coal'
)
sns.lineplot(
    data=DATA,
    x=IDX,
    y='nuclear',
    color=NEUTRAL,
    alpha=ALPHA,
    label='nuclear'
)
sns.lineplot(
    data=DATA,
    x=IDX,
    y='imported',
    color=MEDIUM,
    alpha=ALPHA,
    label='imported'
)
ax.set_ylabel(
```

```
    'billion btus',
    weight='bold'
)
plt.xlabel(
    'date',
    weight='bold'
)
plt.title(
    'Electricity in Georgia by Source 2000-2019',
    weight='bold',
    size='large'
)
ax.legend(loc=2);
```

executed in 359ms, finished 09:39:44 2021-10-22



6.3 Decrease Strain on Power Grid During High Demand Periods

In [166]:
```
overall_mean
```

executed in 4ms, finished 09:39:44 2021-10-22

Out[166]: 57.805474095796676

Overall electricity generation capacity in Georgia is 14,413 mwh (according to GA Power). The Southeast region covers 5 states.

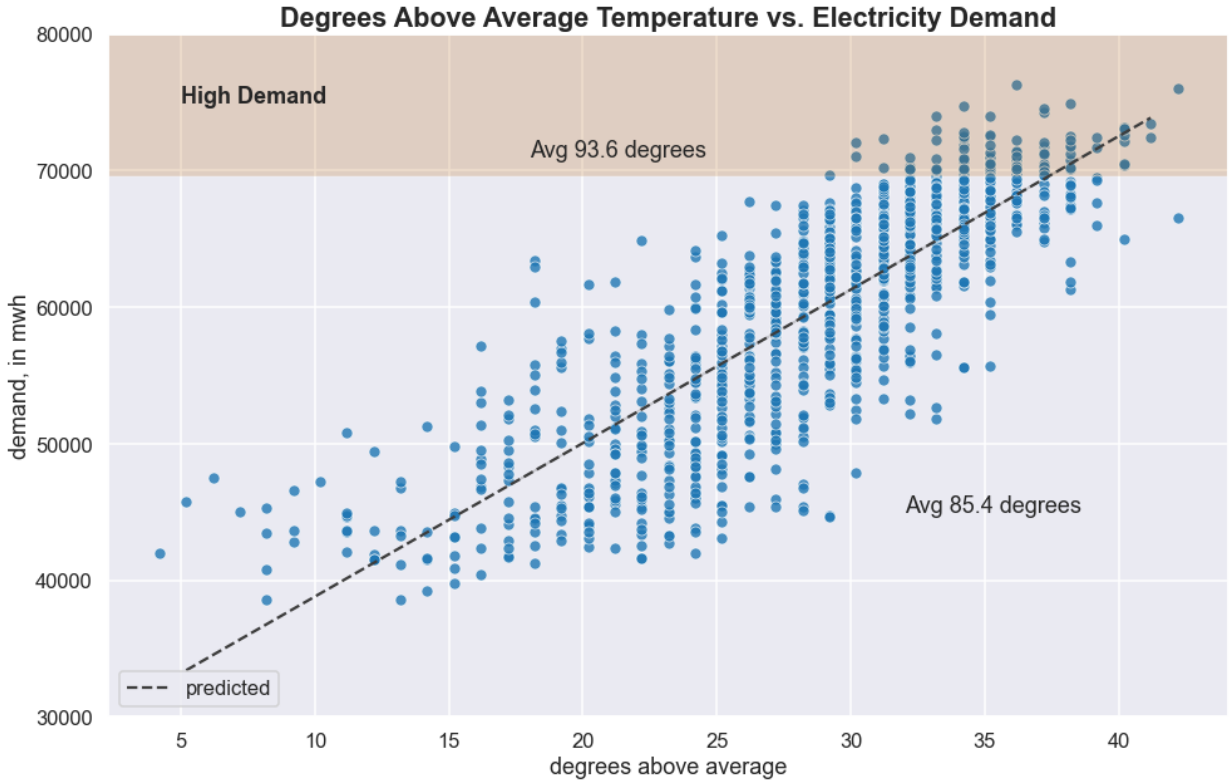
In [167]:
```
#Find the cutoffs for high-demand and hot days
demand_above_df = demand_above_df.copy()
demand_above_df['hot'] = demand_above_df['extreme'] >= 32.2
demand_above_df['high_demand'] = (
    demand_above_df['demand'] >=
    demand_above_df['demand'].quantile(.9)
)

high_demand_avg_temp = round(
    demand_above_df
    [demand_above_df['high_demand']==True]
    ['extreme'].mean() + overall_mean,1
)
lower_demand_avg_temp = round(
    demand_above_df
    [demand_above_df['high_demand']!=True]
    ['extreme'].mean() + overall_mean,1
)

percent_hot = round(demand_above_df['hot'].sum()/climate.shape[0]*100,1)
high_demand_avg_temp, lower_demand_avg_temp, percent_hot
```

executed in 11ms, finished 09:39:44 2021-10-22

Out[167]: (93.6, 85.4, 13.7)

In [168]:
```
#Plot the temperature vs demand
fig,ax = plt.subplots(figsize=(16,10))
sns.lineplot(
    x=X_test_above['extreme'],
    y=pred_test_above,
    color=DARK_NEUTRAL,
    label='predicted',
    linestyle='--'
)
sns.scatterplot(
    data=demand_above_df,
    x='extreme', y='demand',
    palette=NEUTRAL,
    alpha=0.8,
    legend=False
)
ax.axhspan(
    demand_above_df['demand'].quantile(.9),
    80_000,
    facecolor=BRICK,
    alpha=0.2)
plt.ylim(30_000,80_000
        )
plt.xlabel('degrees above average')
plt.ylabel('demand, in mwh')
plt.title(
    'Degrees Above Average Temperature vs. Electricity Demand',
    weight='bold',
    size='large'
)
plt.text(5, 75_000, 'High Demand', weight='bold')
plt.text(18,71_000, f'Avg {high_demand_avg_temp} degrees')
plt.text(32,45_000, f'Avg {lower_demand_avg_temp} degrees');
```

executed in 623ms, finished 09:39:45 2021-10-22



In [169]:
```
#Find the number of days over 90 degrees in the past 6 years
demand_temp.index = pd.to_datetime(demand_temp.index)
demand_temp['year'] = demand_temp.index.year
num_hot_days = []
for yr in demand_temp['year'].unique():
    days = (demand_temp[str(yr)]['max_temp'] > 90).sum()
    num_hot_days.append((yr, days))

num_hot_days
```

executed in 13ms, finished 09:39:45 2021-10-22

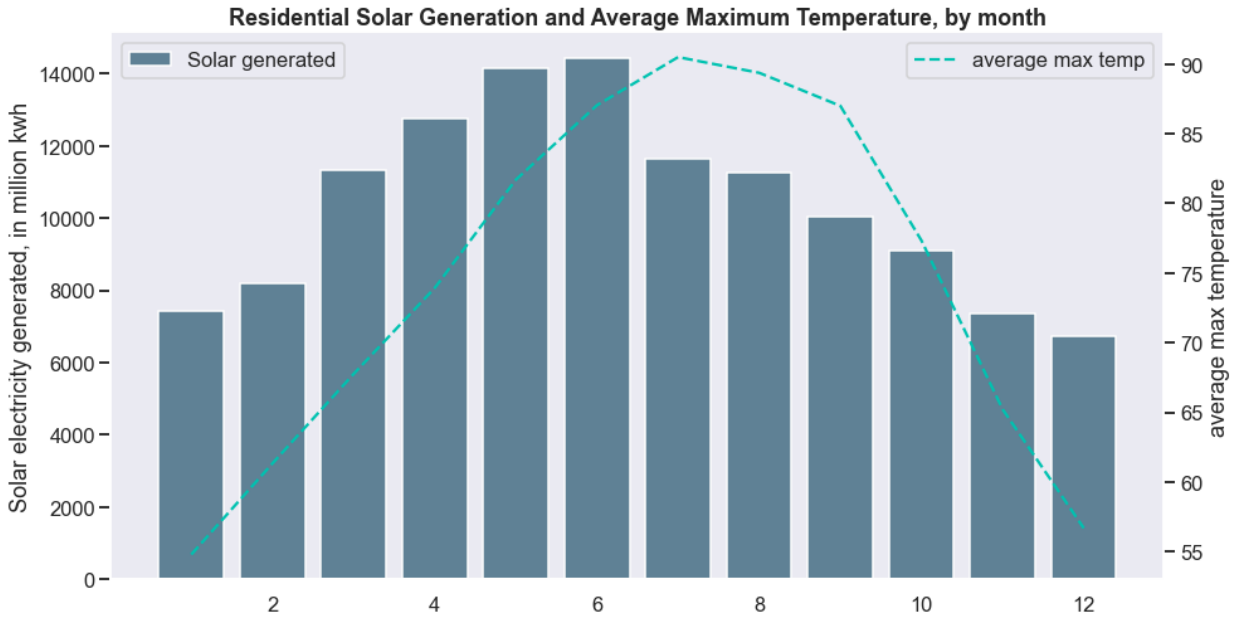
Out[169]:
```
[(2016, 79), (2017, 21), (2018, 45), (2019, 81), (2020, 38), (2021, 19)]
```

In [170]:
```
#Get the temperature averages by month
avg_monthly = climate.copy()
avg_monthly.index = pd.to_datetime(avg_monthly.index)
avg_monthly['month'] = avg_monthly.index.month
avg_monthly = avg_monthly.groupby('month').mean()
avg_monthly.columns = ['avg', 'max', 'min']
us_solar['month'] = us_solar.index.month
solar_monthly = us_solar.groupby('month').sum()
```

executed in 9ms, finished 09:39:45 2021-10-22

In [171]:
```
#Plot the amount of solar generated by month of the year
fig,ax = plt.subplots(figsize=(15,8))
ax.bar(
    x=solar_monthly.index,
    height=solar_monthly['actual'],
    color=NEUTRAL,
    label='Solar generated'
)
plt.legend(loc=2)
ax2=ax.twinx()
avg_monthly['max'].plot(
    color=HIGHLIGHT,
    linestyle='--',
    label='average max temp'
)
ax.set_ylabel('Solar electricity generated, in million kwh')
ax2.set_ylabel('average max temperature')
plt.title(
    'Residential Solar Generation and Average Maximum Temperature, by month
    weight='bold'
)
ax.grid(False)
ax2.grid(False)
plt.legend();
```

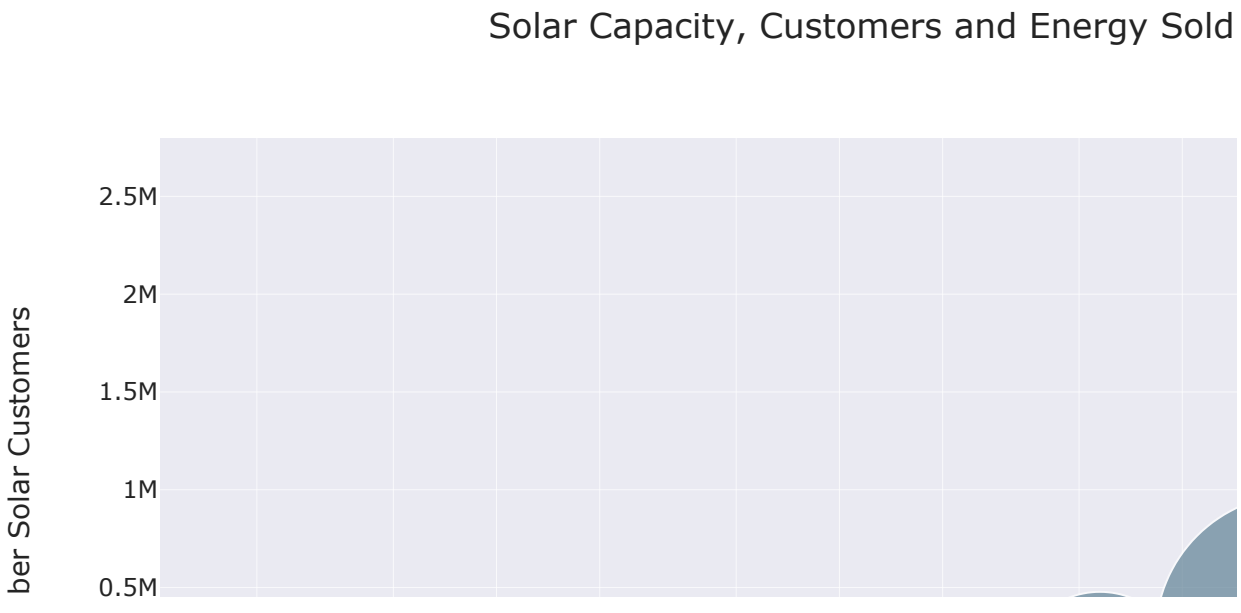
executed in 283ms, finished 09:39:45 2021-10-22



6.4 Stay Competitive With U.S. Market

In [172]:
```
#Plot the relationship between solar customers, capacity and energy sold ba
net_metering_2020['GA'] = net_metering_2020['state'] == 'GA'

net_metering_nocal = net_metering_2020[net_metering_2020['state'] != 'CA']
fig = px.scatter(
    net_metering_nocal,
    x="residential_solar_capacity",
    y="residential_solar_customers",
    size="energy_sold",
    hover_name="state",
    color='GA',
    template='seaborn',
    log_x=True,
    size_max=100,
    title='Solar Capacity, Customers and Energy Sold Back by State',
    labels={ "GA":
            'Georgia?',
            "residential_solar_capacity":
            'Solar capacity, million kwh (log-scale)',
            "residential_solar_customers":
            "Number Solar Customers"
            },
    color_discrete_map={
                True: HIGHLIGHT, False: NEUTRAL},
    hover_data= {'GA':False,
                'residential_solar_capacity':':.2f',
                'residential_solar_customers':':.2f',
                'energy_sold':':.2f'})
fig.add_annotation(
    text="Georgia", x=1.41, y=2613, arrowhead=1, showarrow=True)

fig.show()
```

executed in 800ms, finished 09:39:46 2021-10-22

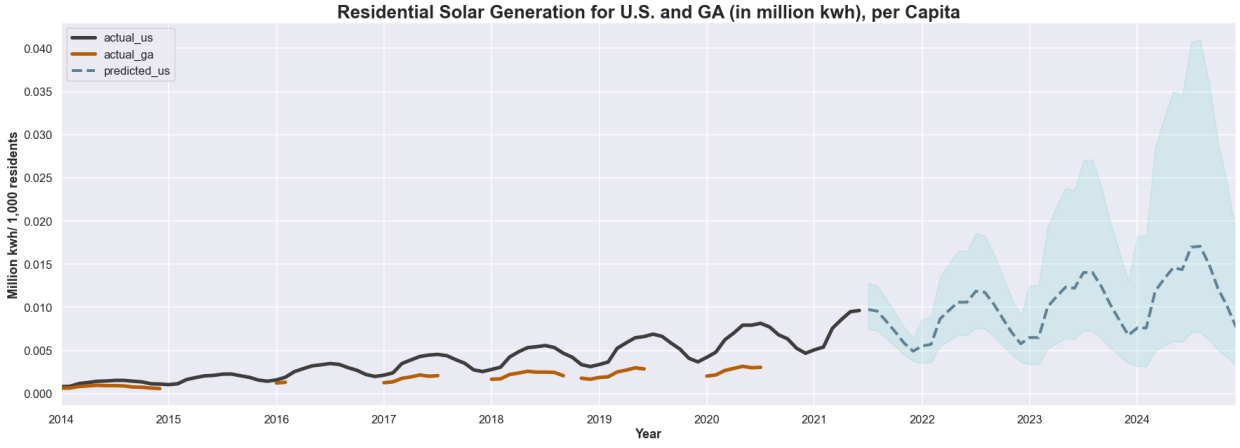


In [173]:
```
#Convert to millon kwh/1000 people for GA and US solar generation
future_solar = us_solar.copy()
future_solar = pd.concat(
    [us_solar['2014':],
     np.e**(solar_SARIMA_fcast['2021-07-01':])],
    axis=0
)
future_solar['ga'] = pd.DataFrame(ga_solar)[:-1]

future_solar.drop(['mean_se','month'], axis=1, inplace=True)
future_solar.columns = ([
    'actual_us',
    'predicted_us',
    'lower_ci',
    'upper_ci',
    'actual_ga'
])

# In million kwh
us_pop = 329_500_000
ga_pop = 10_600_000

for col in future_solar.columns[:4]:
    future_solar[col] = future_solar[col] * 1_000/ us_pop

future_solar['actual_ga'] = future_solar['actual_ga'] * 1_000/ ga_pop
```

executed in 13ms, finished 09:39:46 2021-10-22

In [174]:
```
#Plot the data
fig,ax = plt.subplots(figsize=(30,10))
future_solar['actual_us'].plot(
    ax=ax,
    color=DARK_NEUTRAL,
    lw=5
)
future_solar['actual_ga'].plot(
    ax=ax,
    color=BRICK,
    lw=5
)
future_solar['predicted_us'].plot(
    ax=ax,
    color=NEUTRAL,
    linestyle='dashed',
    lw=4
)

ax.fill_between(
    future_solar.index,
    future_solar['lower_ci'],
    future_solar['upper_ci'],
    color=HIGHLIGHT,
    alpha=0.1
)
plt.title(
    'Residential Solar Generation for U.S. and GA (in million kwh), per Cap
    weight='bold',
    size='x-large'
)
plt.xlabel(
    'Year',
    weight='bold'
)
plt.ylabel(
    'Million kwh/ 1,000 residents',
    weight='bold'
)
ax.legend(loc=2);
```

executed in 475ms, finished 09:39:46 2021-10-22



7 Conclusions

By eliminating the cap on the number of residential customers that can benefit from the net-metering program, Georgia will encourage more homeowners to install PV systems.

7.1 Georgia faces increased dependence on imported electricity

7.1.1 Model Evaluation

The best model was an AR model with a first difference, a lag of 5 and a linear trend component. Although it failed to pick up on the temporary fluctuations on residential energy demand during Covid, it generalizes well and has an RMSE of 0.01 billion btus (the naive model had an RMSE of 0.085).

7.1.2 What the Data Say

The AR model predicts a 5% increase in residential energy demand from 2021 to 2023. The last year that data were available about energy sources was 2019, and at that point, 8% of electricity was imported and that amount has overall been increasing since 1995. Additionally, since Georgia does not have any coal, natural gas, uranium or petroleum resources, the raw materials for these electricity sources also have to be imported.

7.1.3 How an Increase in Residential Solar Can Help

The population of Georgia is increasing and with it, so is the demand for electricity. Since renewable sources (including solar) are the only methods which do not rely on the import of fuel sources, increasing that sector reduces Georgia's dependence on other state's for its electricity needs.

7.2 An Increase in Natural Gas Prices Leads to Greater Electricity Costs

7.2.1 Model Evaluation

The best SARIMA model had an order of (0,0,0) and a seasonal order of (2,2,2,52). This shows that it finding a pattern between the prices two years ago (104 weeks) and the current price. The RMSE was 0.291, which is not a great improvement from the naive model of 0.425. The confidence intervals are very broad, showing that the model does not have much certainty in its predictions.

The best LSTM has two bidirectional layers and two dense layers, one with regularization. The RMSE of 0.07 on the rolling predictions was much better than the SARIMA model, but the plot shows that it is not doing an effective job of capturing the patterns in the data.

7.2.2 What the Data Say

Since none of the models were accurate at forecasting, it is a sign that gas prices are dependent on exogenous variables, rather than being autoregressive.

7.2.3 How an Increase in Residential Solar Can Help

Natural gas prices fluctuate quite a bit, from a low of $1.41 to a high of $14.74 in the last 27 years (standard deviation of $2.24). In addition, Georgia's use of natural gas to produce electricity has increased more than 124% in that same period. In order to keep electricity costs low, Georgia should shift to other sources, including solar.

7.3 Extreme High Temperatures Strain the Electrical Grid

7.3.1 Model Evaluation

The model is a simple OLS model with a single predictor (temperature). The RMSE values were very close between the train and test sets (4,674 and 4,871 mwh respectively), showing that the model is not overfitting.

The R2 of the test data is 0.69, indicating that 69% of the residential electricity demand can be explained by the number of degrees over average of the outside temperature.

The intercept of 26,540 indicates that on a day with an average temperature of 57.8 degrees, the electricity demand in the Southeast region is 28,110 mwh. The coefficient of 1,157 indicates that for every degree above normal, there is an additional demand on the grid of 1,157 mwh.

The data fit the assumptions for linear regression with a Durbin-Watson score of just under 2 , showing no autocorrelation and indicating that the residuals are homoscedastic. The kurtosis value of just over 3 shows slightly heavier tails than a normal distribution.

7.3.2 What the Data Say

The average temperature during the top 10% of electricity demand is 93.6 degrees. Those temperatures are not unusual for Georgia.

In [175]:
```
for year in num_hot_days:
    print(f'-In {year[0]} there were {year[1]} days over 90 degrees.')
```

executed in 4ms, finished 09:39:46 2021-10-22

```
-In 2016 there were 79 days over 90 degrees.
-In 2017 there were 21 days over 90 degrees.
-In 2018 there were 45 days over 90 degrees.
-In 2019 there were 81 days over 90 degrees.
-In 2020 there were 38 days over 90 degrees.
-In 2021 there were 19 days over 90 degrees.
```

Whenever the demand on the grid is high, there is a risk of rolling blackouts or grid collapse, both of which cause hardship on residents and cost the state money in repairs and imported electricity.

7.3.3 How an Increase in Residential Solar Can Help

When solar is generated at the source, it does not rely on the grid to power a residence. On sunny days, a residential PV system can generate enough power to provide electricity for other homes. Cobb County EMC, which has net metering, states that up to 30% of their electricity comes from solar on sunny days. If residential solar is increased, the overall demand on the grid (especially on sunny days in the spring and summer), will decrease.

7.4 Georgia is Falling Behind the U.S. in Energy

7.4.1 Model Evaluation

The best model was a SARIMA model with an order of (0,0,0) and a seasonal order of (2,2,2,12). This indicates that the model is predicting from the values and errors two years (24 months) ago. The RMSE is 0.123, which is greatly improved from the naive model's RMSE of 4.833.

The residuals are relatively normal with the exception of some outliers. The correlogram suggests that there is information that the model is not capturing, but the forecast plot seems to describe the data well.

7.4.2 What the Data Say

When looking at the per capita production of residential solar electricity, it is clear that Georgia is lagging behind the U.S. In looking at the individual states, there is a clear correlation between the number of solar customers, the residential solar capacity and the energy sold back to the grid via net-metering programs. Georgia is towards the bottom in all three areas.

7.4.3 How an Increase in Residential Solar Can Help

With energy prices generally rising and an increased concern for protecting the environment, there will likely be increased pressure at the federal level to keep up with the changing energy landscape. Increasing residential solar production is one step Georgia can take in this direction.

8 Summary of Conclusions

Remove the cap on net metering to encourage more residential PV solar systems. Increasing the amount of residential solar in Georgia will:

- Increase independence from imported fuel sources by increasing renewable energy sources (including solar)
- Lower costs associated with natural gas by increasing energy from other sources (including solar)
- Reduce risk of grid collapse by reducing the strain on the grid, especially during periods of above-average temperatures
- Stay competitive with energy changes by instituting policies that encourage growth and innovation

9 Future Work

- Research impact of different approaches of net-metering programs on customer participation and energy sold back to the power company
- Add exogenous variables to improve model to predict natural gas prices
- Obtain more recent data from Georgia Power to provide a better picture of the current energy situation.