time-series-analysis-us-vaccine-goal (/github/kcoop610/time-series-analysis-us-vaccine-goal/tree/main) / report.ipynb (/github/kcoop610/time-series-analysis-us-vaccine-goal/tree/main/report.ipynb)

Introduction

US COVID-19 Vaccine Administration

On May 4, 2021, United States President Biden announced a goal to administer at least one coronavirus vaccine shot to 70% of the U.S. adult population by July 4th. Read the official statement here. (https://www.whitehouse.gov/briefing-room/statements-releases/2021/05/04/fact-sheet-president-biden-to-announce-goal-to-administer-at-least-one-vaccine-shot-to-70-of-the-u-s-adult-population-by-july-4th/)

Per the briefing, the White House's vaccine campaign actions to reach this goal include:

- **Making access to vaccinations more convenient** by increasing walk-in vaccinations at local pharmacies across the nation and moving to smaller, community-based and mobile vaccination clinics
- **Supporting community vaccine education and local outreach efforts** by expanding the workforce of community-based organizations, supporting underserved communities with the tools needed to get vaccinated, and supporting the next phase of state and local vaccine outreach efforts
- **Providing easier access to those living in rural communities and bolster efforts to reach rural Americans in the response** by shipping new allocations of vaccine to rural health clinicas, increasing vaccine education and outreach efforts in rural communities, and increasing funding for rural health clinics and hospitals to respond to COVID-19 with testing and mitigation measures
- **Launch a comprehensive plan to vaccinate the nation’s adolescents, should the FDA authorize a vaccine for younger ages**

Here we will perform a time series analysis on the CDC's public vaccine distribution and administration dataset as of June 13, 2021 to predict whether or not the US will meet the target, then provide the Biden Administration a set of recommended actions to take in the final 3 weeks in order to reach the goal.

In [96]:

```
# style notebook
from IPython.core.display import HTML
def css_styling():
    styles = open("./styles/custom.css", "r").read()
    return HTML(styles)
css_styling()
```

Out[96]:

In [2]:
```
#import standard packages
import pandas as pd
pd.set_option('display.max_columns', 0)
import numpy as np

#import viz packages
import matplotlib.pyplot as plt
%matplotlib inline
plt.rcParams['figure.figsize'] = (15,5) #setting figures to timeseries·
import plotly.express as px
import plotly.graph_objects as go

#import time series tools from statsmodels
import statsmodels.tsa.api as tsa
import statsmodels
print(f'Statsmodels version = {statsmodels.__version__}')

#import custom functions from .py file
import functions as func
```

```
Statsmodels version = 0.12.0
```

Data Source

Data for this analysis was sourced from the CDC's official COVID-19 Vaccination dataset (https://data.cdc.gov/Vaccinations/COVID-19-Vaccinations-in-the-United-States-Jurisdi/unsk-b7fc), on June 13, 2021.

Description of the data source:

> Overall US COVID-19 Vaccine deliveries and administration data at national and jurisdiction level. Data represents all vaccine partners including jurisdictional partner clinics, retail pharmacies, long-term care facilities, dialysis centers, Federal Emergency Management Agency and Health Resources and Services Administration partner sites, and federal entity facilities.

Notes on source data

- "Adults" defined as age 18+
- To estimate the 12+, 18+ and 65+ populations for US territories, CDC assumes that the proportions of people aged 12 years and older, 18 years and older and people aged 65 years and older in the territories are the same as in the aggregate of the 50 states, DC, and Puerto Rico (85%, 78% and 17%, respectively).
- Vaccination data on CDC’s COVID Data Tracker are typically at least 48 hours behind a state’s vaccination data reports.
- This analysis focuses on the 50 states, District of Columbia, and Puerto Rico

In [3]:

```
#load the full dataset
full_dataset = pd.read_csv('./data/COVID-19_Vaccinations_in_the_United_
full_dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 11798 entries, 0 to 11797
Data columns (total 69 columns):
 #   Column                                Non-Null Count  Dtype  
---  ------                                --------------  -----  
 0   Date                                  11798 non-null  object 
 1   MMWR_week                             11798 non-null  int64  
 2   Location                              11798 non-null  object 
 3   Distributed                           11798 non-null  int64  
 4   Distributed_Janssen                   11798 non-null  int64  
 5   Distributed_Moderna                   11798 non-null  int64  
 6   Distributed_Pfizer                    11798 non-null  int64  
 7   Distributed_Unk_Manuf                 11798 non-null  int64  
 8   Dist_Per_100K                         11798 non-null  int64  
 9   Distributed_Per_100k_12Plus           11798 non-null  int64  
 10  Distributed_Per_100k_18Plus           11798 non-null  int64  
 11  Distributed_Per_100k_65Plus           11798 non-null  int64  
 12  Administered                          11798 non-null  int64  
 13  Administered_12Plus                   11798 non-null  int64  
 14  Administered_18Plus                   11798 non-null  int64  
 15  Administered_65Plus                   11798 non-null  int64  
 16  Administered_Janssen                  11798 non-null  int64  
 17  Administered_Moderna                  11798 non-null  int64  
 18  Administered_Pfizer                   11798 non-null  int64  
 19  Administered_Unk_Manuf                11798 non-null  int64  
 20  Administered_Fed_LTC                  11798 non-null  int64  
 21  Administered_Fed_LTC_Residents        11798 non-null  int64  
 22  Administered_Fed_LTC_Staff            11798 non-null  int64  
 23  Administered_Fed_LTC_Unk              11798 non-null  int64  
 24  Administered_Fed_LTC_Dose1            11798 non-null  int64  
 25  Administered_Fed_LTC_Dose1_Residents  11798 non-null  int64  
 26  Administered_Fed_LTC_Dose1_Staff      11798 non-null  int64  
 27  Administered_Fed_LTC_Dose1_Unk        11798 non-null  int64  
 28  Admin_Per_100K                        11798 non-null  int64  
 29  Admin_Per_100k_12Plus                 11798 non-null  int64  
 30  Admin_Per_100k_18Plus                 11798 non-null  int64  
 31  Admin_Per_100k_65Plus                 11798 non-null  int64  
 32  Recip_Administered                    11798 non-null  int64  
 33  Administered_Dose1_Recip              11798 non-null  int64  
 34  Administered_Dose1_Pop_Pct            11798 non-null  float64
 35  Administered_Dose1_Recip_12Plus       11798 non-null  int64  
 36  Administered_Dose1_Recip_12PlusPop_Pct  11798 non-null  float64
 37  Administered_Dose1_Recip_18Plus       11798 non-null  int64  
 38  Administered_Dose1_Recip_18PlusPop_Pct  11798 non-null  float64
 39  Administered_Dose1_Recip_65Plus       11798 non-null  int64  
 40  Administered_Dose1_Recip_65PlusPop_Pct  11798 non-null  float64
 41  Series_Complete_Yes                   11798 non-null  int64  
 42  Series_Complete_Pop_Pct               11798 non-null  float64
 43  Series_Complete_12Plus                11798 non-null  int64  
 44  Series_Complete_12PlusPop_Pct         11798 non-null  float64
 45  Series_Complete_18Plus                11798 non-null  int64  
 46  Series_Complete_18PlusPop_Pct         11798 non-null  float64
```

```
 47  Series_Complete_65Plus                    11798 non-null  int64
 48  Series_Complete_65PlusPop_Pct             11798 non-null  float64
 49  Series_Complete_Janssen                   11798 non-null  int64
 50  Series_Complete_Moderna                   11798 non-null  int64
 51  Series_Complete_Pfizer                    11798 non-null  int64
 52  Series_Complete_Unk_Manuf                 11798 non-null  int64
 53  Series_Complete_Janssen_12Plus            11798 non-null  int64
 54  Series_Complete_Moderna_12Plus            11798 non-null  int64
 55  Series_Complete_Pfizer_12Plus             11798 non-null  int64
 56  Series_Complete_Unk_Manuf_12Plus          11798 non-null  int64
 57  Series_Complete_Janssen_18Plus            11798 non-null  int64
 58  Series_Complete_Moderna_18Plus            11798 non-null  int64
 59  Series_Complete_Pfizer_18Plus             11798 non-null  int64
 60  Series_Complete_Unk_Manuf_18Plus          11798 non-null  int64
 61  Series_Complete_Janssen_65Plus            11798 non-null  int64
 62  Series_Complete_Moderna_65Plus            11798 non-null  int64
 63  Series_Complete_Pfizer_65Plus             11798 non-null  int64
 64  Series_Complete_Unk_Manuf_65Plus          11798 non-null  int64
 65  Series_Complete_FedLTC                    11798 non-null  int64
 66  Series_Complete_FedLTC_Residents          11798 non-null  int64
 67  Series_Complete_FedLTC_Staff              11798 non-null  int64
 68  Series_Complete_FedLTC_Unknown            11798 non-null  int64
dtypes: float64(8), int64(59), object(2)
memory usage: 6.2+ MB
```

There are no null values in the dataset.

EDA & Preprocessing

Next step is to explore the data, understand trends within, engineer a "region" feature, and slice the data into subsets for analysis.

Steps:

1. Select feature to analyze
2. Convert date feature to datetime data type
3. Process out some locations
4. Feature engineering
5. Create dataframes for 3 analyses: National, by State, by Region
6. Visualize the trend in vaccine administration as of 6/13/2021 for each of the 3 subsets

---

Select Feature To Analyze

In [4]:
```
#review columns, referencing column definitions:
    #https://data.cdc.gov/Vaccinations/COVID-19-Vaccinations-in-the-Un:
full_dataset.columns
```

Out[4]:
```
Index(['Date', 'MMWR_week', 'Location', 'Distributed', 'Distributed_Ja:
       'Distributed_Moderna', 'Distributed_Pfizer', 'Distributed_Unk_Ma
       'Dist_Per_100K', 'Distributed_Per_100k_12Plus',
       'Distributed_Per_100k_18Plus', 'Distributed_Per_100k_65Plus',
       'Administered', 'Administered_12Plus', 'Administered_18Plus',
       'Administered_65Plus', 'Administered_Janssen', 'Administered_Mo
       'Administered_Pfizer', 'Administered_Unk_Manuf', 'Administered_]
       'Administered_Fed_LTC_Residents', 'Administered_Fed_LTC_Staff',
       'Administered_Fed_LTC_Unk', 'Administered_Fed_LTC_Dose1',
       'Administered_Fed_LTC_Dose1_Residents',
       'Administered_Fed_LTC_Dose1_Staff', 'Administered_Fed_LTC_Dose1_
       'Admin_Per_100K', 'Admin_Per_100k_12Plus', 'Admin_Per_100k_18Plu
       'Admin_Per_100k_65Plus', 'Recip_Administered',
       'Administered_Dose1_Recip', 'Administered_Dose1_Pop_Pct',
       'Administered_Dose1_Recip_12Plus',
       'Administered_Dose1_Recip_12PlusPop_Pct',
       'Administered_Dose1_Recip_18Plus',
       'Administered_Dose1_Recip_18PlusPop_Pct',
       'Administered_Dose1_Recip_65Plus',
       'Administered_Dose1_Recip_65PlusPop_Pct', 'Series_Complete_Yes',
       'Series_Complete_Pop_Pct', 'Series_Complete_12Plus',
       'Series_Complete_12PlusPop_Pct', 'Series_Complete_18Plus',
       'Series_Complete_18PlusPop_Pct', 'Series_Complete_65Plus',
       'Series_Complete_65PlusPop_Pct', 'Series_Complete_Janssen',
       'Series_Complete_Moderna', 'Series_Complete_Pfizer',
       'Series_Complete_Unk_Manuf', 'Series_Complete_Janssen_12Plus',
       'Series_Complete_Moderna_12Plus', 'Series_Complete_Pfizer_12Plus
       'Series_Complete_Unk_Manuf_12Plus', 'Series_Complete_Janssen_18]
       'Series_Complete_Moderna_18Plus', 'Series_Complete_Pfizer_18Plus
       'Series_Complete_Unk_Manuf_18Plus', 'Series_Complete_Janssen_65]
       'Series_Complete_Moderna_65Plus', 'Series_Complete_Pfizer_65Plus
       'Series_Complete_Unk_Manuf_65Plus', 'Series_Complete_FedLTC',
       'Series_Complete_FedLTC_Residents', 'Series_Complete_FedLTC_Sta:
       'Series_Complete_FedLTC_Unknown'],
      dtype='object')
```

Of the features available, the one that matches most closely to the goal is **Administered_Dose1_Recip_18PlusPop_Pct,** which represents the percent of adult (18+) population with at lease one dose based on the jurisdiction where recipient lives.

In [5]:

```
#create a dataframe with only the target feature, date, and location
ts1 = full_dataset[['Date', 'Location', 'Administered_Dose1_Recip_18Plu
ts1.head()
```

Out[5]:

	Date	Location	Administered_Dose1_Recip_18PlusPop_Pct
0	06/13/2021	ND	54.6
1	06/13/2021	DE	68.1
2	06/13/2021	GA	52.2
3	06/13/2021	WA	71.5
4	06/13/2021	NM	72.6

Convert Date Feature to `datetime` Data Type

In [6]:

```
# convert Date column to datetime data type
ts1['Date'] = pd.to_datetime(ts1['Date'])
```

```
<ipython-input-6-a2d07396e975>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
  ts1['Date'] = pd.to_datetime(ts1['Date'])
```

In [7]:

```
ts1.set_index('Date', inplace=True)
```

In [8]:

```
ts1
```

Out[8]:

	Location	Administered_Dose1_Recip_18PlusPop_Pct
Date		
2021-06-13	ND	54.6
2021-06-13	DE	68.1
2021-06-13	GA	52.2
2021-06-13	WA	71.5
2021-06-13	NM	72.6
...	...	...
2020-12-13	US	0.0
2020-12-13	GU	0.0
2020-12-13	AS	0.0
2020-12-13	VI	0.0
2020-12-13	LTC	0.0

11798 rows × 2 columns

Process Out Some Locations

This analysis will focus on the 50 US states, DC, and Puerto Rico. Other jurisdictions included in the original dataset are US-owned teritories and federal entities.

In [9]:

```
#explore jurisdictions represented in the dataset
locs = sorted(list(ts1.Location.unique()))
print(len(locs)) #goal: 52
print(locs)
```

```
65
['AK', 'AL', 'AR', 'AS', 'AZ', 'BP2', 'CA', 'CO', 'CT', 'DC', 'DD2', 'I
```

In [10]:
```
#remove US territories
locs.remove('AS') #remove American Samoa
locs.remove('FM') #remove Federated States of Micronesia
locs.remove('GU') #remove Guam
locs.remove('MH') #remove Marshall Islands
locs.remove('MP') #remove Northern Mariana Islands
locs.remove('RP') #remove Palau
locs.remove('VI') #remove US Virgin Islands
#remove federal entities
locs.remove('BP2') #bureau of prisons
locs.remove('DD2') #dept of defense
locs.remove('IH2') #indian health services
locs.remove('LTC') #long term care
locs.remove('VA2') #veterans health
#remove US total to use this as a list of the sub-jurisdictions
locs.remove('US')
```

In [11]:
```
print(len(locs))
print(locs)
```

```
52
['AK', 'AL', 'AR', 'AZ', 'CA', 'CO', 'CT', 'DC', 'DE', 'FL', 'GA', 'HI
```

Create Dataframes & Visualizations To Analyze National Trends, Trends By State, & Trends By Region

National Vaccine Administration

In [12]:

```
# parse out the national data for modeling & analysis
ts1_national = ts1[ts1['Location'] == 'US']
ts1_national.drop(columns='Location', inplace=True)
# set frequency to days
ts1_national=ts1_national.resample('D').asfreq()
ts1_national
```

```
/Users/kristincooper/opt/anaconda3/envs/learn-env/lib/python3.8/site-pa
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
  return super().drop(
```

Out[12]:

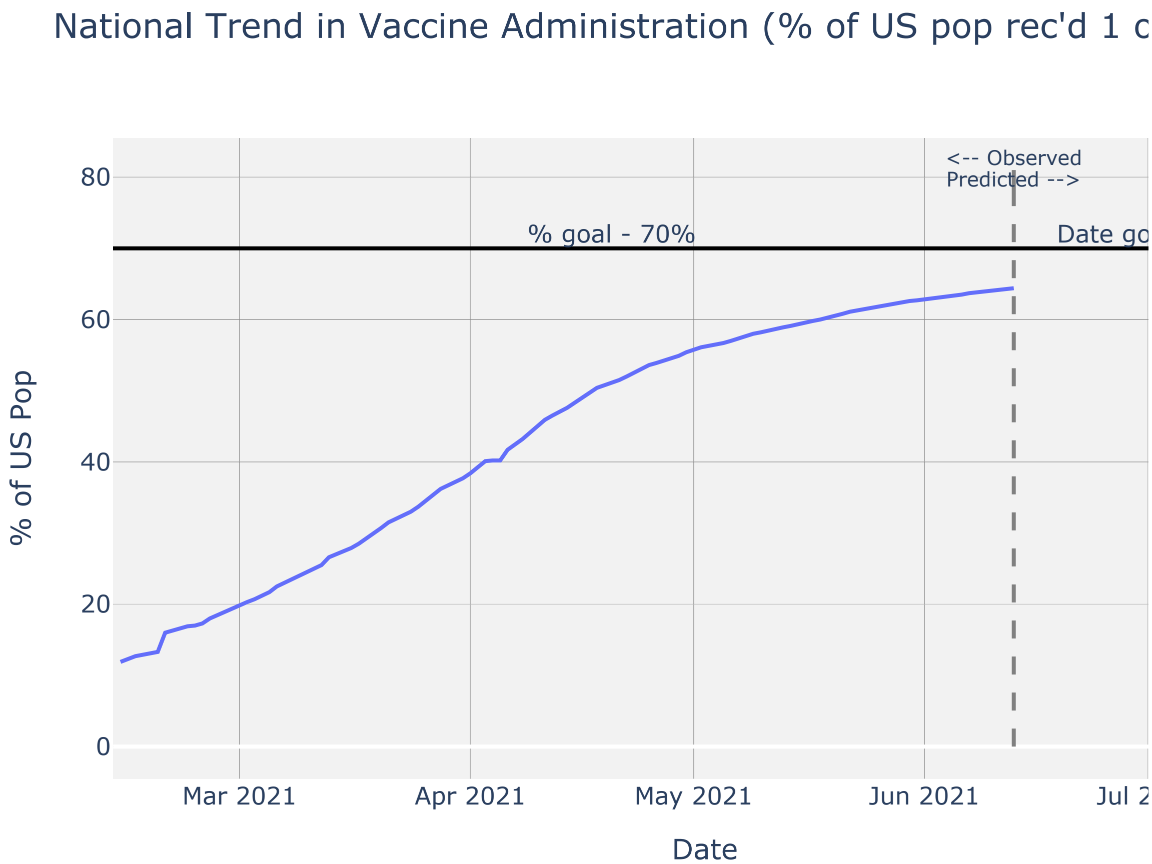
	Administered_Dose1_Recip_18PlusPop_Pct
Date	
2020-12-13	0.0
2020-12-14	0.0
2020-12-15	0.0
2020-12-16	0.0
2020-12-17	0.0
...	...
2021-06-09	63.9
2021-06-10	64.0
2021-06-11	64.1
2021-06-12	64.3
2021-06-13	64.4

183 rows × 1 columns

In [13]:

```
#start analysis when reported #'s exceed 0 so as to not confuse the moc
ts1_national = ts1_national[ts1_national['Administered_Dose1_Recip_18P]
```

In [14]:
```
# plot national trend
func.plot_vax(ts=ts1_national,
         title="National Trend in Vaccine Administration (% of US pop r
         labels={'value': '% of US Pop', 'variable': 'Legend'})
```



Vaccine Administration by State

In [15]:

```
# create a separate dataframe with only the 50 states + DC + PR
ts1_states = ts1[ts1['Location'] == locs[0]]
for x in locs[1:]:
    ts1_states = pd.concat([ts1_states, ts1[ts1['Location'] == x]], axi
ts1_states
```

Out[15]:

	Location	Administered_Dose1_Recip_18PlusPop_Pct
Date		
2021-06-13	AK	59.5
2021-06-12	AK	59.4
2021-06-11	AK	59.3
2021-06-10	AK	59.2
2021-06-09	AK	59.1
...	...	...
2020-12-18	WY	0.0
2020-12-17	WY	0.0
2020-12-16	WY	0.0
2020-12-15	WY	0.0
2020-12-14	WY	0.0

9464 rows × 2 columns

In [16]:

```
# set frequency to days
ts1_states = ts1_states.groupby('Location').resample('D').asfreq()
ts1_states
```

Out[16]:

		Location	Administered_Dose1_Recip_18PlusPop_Pct
Location	**Date**		
AK	**2020-12-14**	AK	0.0
	2020-12-15	AK	0.0
	2020-12-16	AK	0.0
	2020-12-17	AK	0.0
	2020-12-18	AK	0.0
...	**...**	...	...
WY	**2021-06-09**	WY	47.9
	2021-06-10	WY	47.9
	2021-06-11	WY	47.9
	2021-06-12	WY	48.1
	2021-06-13	WY	48.2

9464 rows × 2 columns

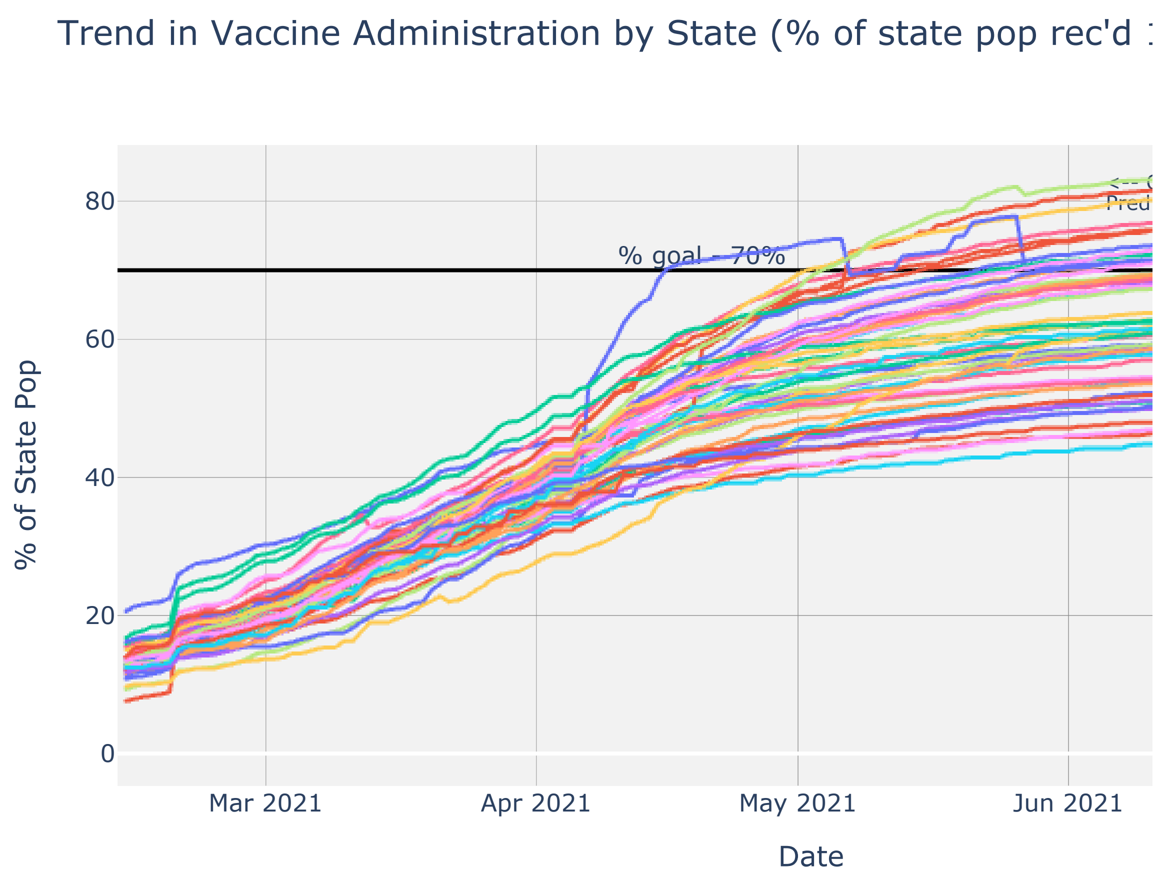
In [17]:

```
ts1_states = ts1_states.drop(columns='Location').reset_index().set_inde
```

In [18]:

```
# start when doses administered > 0
ts1_states = ts1_states[ts1_states['Administered_Dose1_Recip_18PlusPop_
```

In [19]:
```
# visualize states
func.plot_vax(ts1_states, color='Location',
              title="Trend in Vaccine Administration by State (% of sta
              labels={'value': '% of State Pop'})
```



Vaccine Administration by Region

In [20]:
```
#create region lists
northeast = ['CT', 'ME', 'MA', 'NH', 'RI', 'VT', 'NJ', 'NY', 'PA']
midwest = ['IN', 'IL', 'MI', 'OH', 'WI', 'IA', 'KS', 'MN', 'MO', 'NE',
south = ['DE', 'DC', 'FL', 'GA', 'MD', 'NC', 'SC', 'VA', 'WV', 'AL', 'K
         'AR', 'LA', 'OK', 'TX', 'PR']
west = ['AZ', 'CO', 'ID', 'NM', 'MT', 'UT', 'NV', 'WY', 'AK', 'CA', 'HI

#check that all 52 locations are captured in a list
len(northeast+midwest+south+west)
```

Out[20]:
```
52
```

In [21]:
```
#define function to determine region given state, to use in a lambda fu
def region(state):
    region = str()
    if state in northeast:
        region = 'Northeast'
    if state in midwest:
        region = 'Midwest'
    if state in south:
        region = 'South'
    if state in west:
        region = 'West'
    return region
```

In [22]:
```
#check the function works as intended
region(ts1_states.Location[0])
```

Out[22]:
```
'West'
```

In [23]:
```
#map function to all rows in the states df
ts1_region = ts1_states.copy()
ts1_region['Region'] = ts1_region.Location.map(lambda x: region(x))
```

In [24]:
```
#check that the map function worked
ts1_region.Region.value_counts()
```

Out[24]:
```
South        2166
West         1573
Midwest      1452
Northeast    1089
Name: Region, dtype: int64
```

In [25]:

```
ts1_region = ts1_region.drop(columns='Location')
ts1_region
```

Out[25]:

	Administered_Dose1_Recip_18PlusPop_Pct	Region
Date		
2021-02-13	20.6	West
2021-02-14	21.3	West
2021-02-15	21.6	West
2021-02-16	21.8	West
2021-02-17	22.0	West
...	...	...
2021-06-09	47.9	West
2021-06-10	47.9	West
2021-06-11	47.9	West
2021-06-12	48.1	West
2021-06-13	48.2	West

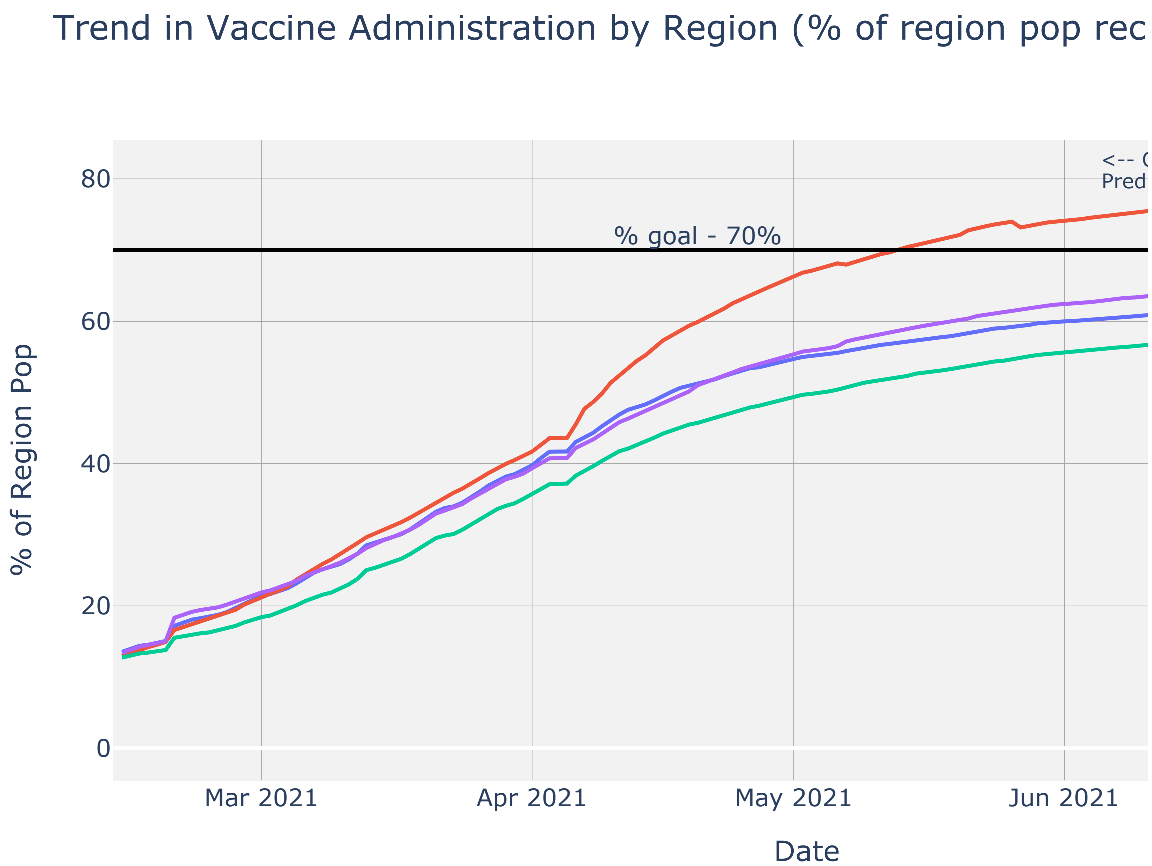
6280 rows × 2 columns

In [26]:

```
# group by date, then region to get trends per region
ts1_region = ts1_region.reset_index().groupby(['Date', 'Region']).mean(
```

In [27]:

```
# visualize regional trends
func.plot_vax(ts1_region, color='Region',
              title="Trend in Vaccine Administration by Region (% of re
              labels={'value': '% of Region Pop'})
```



National Analysis

In [28]:
```
ts1_national
```

Out[28]:

	Administered_Dose1_Recip_18PlusPop_Pct
Date	
2021-02-13	11.9
2021-02-14	12.4
2021-02-15	12.7
2021-02-16	12.9
2021-02-17	13.1
...	...
2021-06-09	63.9
2021-06-10	64.0
2021-06-11	64.1
2021-06-12	64.3
2021-06-13	64.4

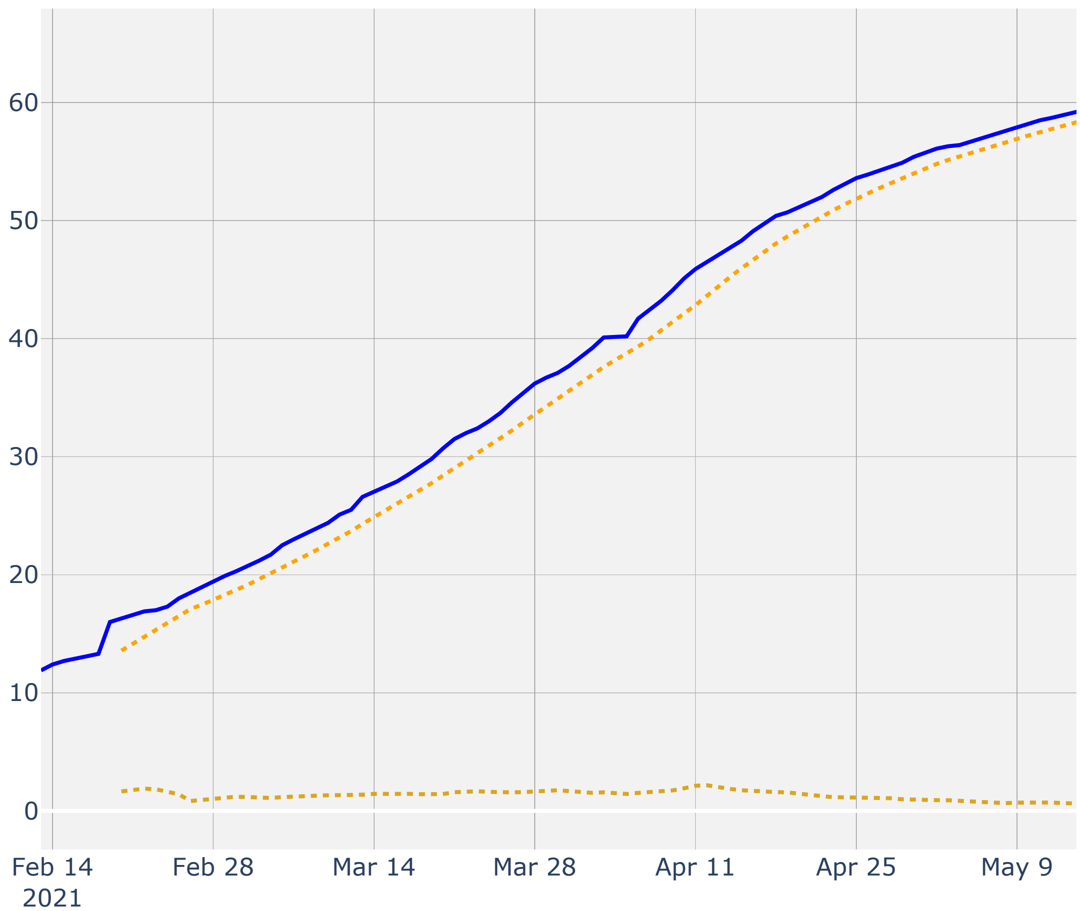
121 rows × 1 columns

In [29]:

```
#visualize rolling mean, calculate stationarity
func.stationarity_check(ts1_national)
```

	Test Stat	p-value	k-lags	n-observations	Stationary?
AD Fuller Test	-1.493298	0.536824	7	113	False

Rolling Mean & Standard Deviation



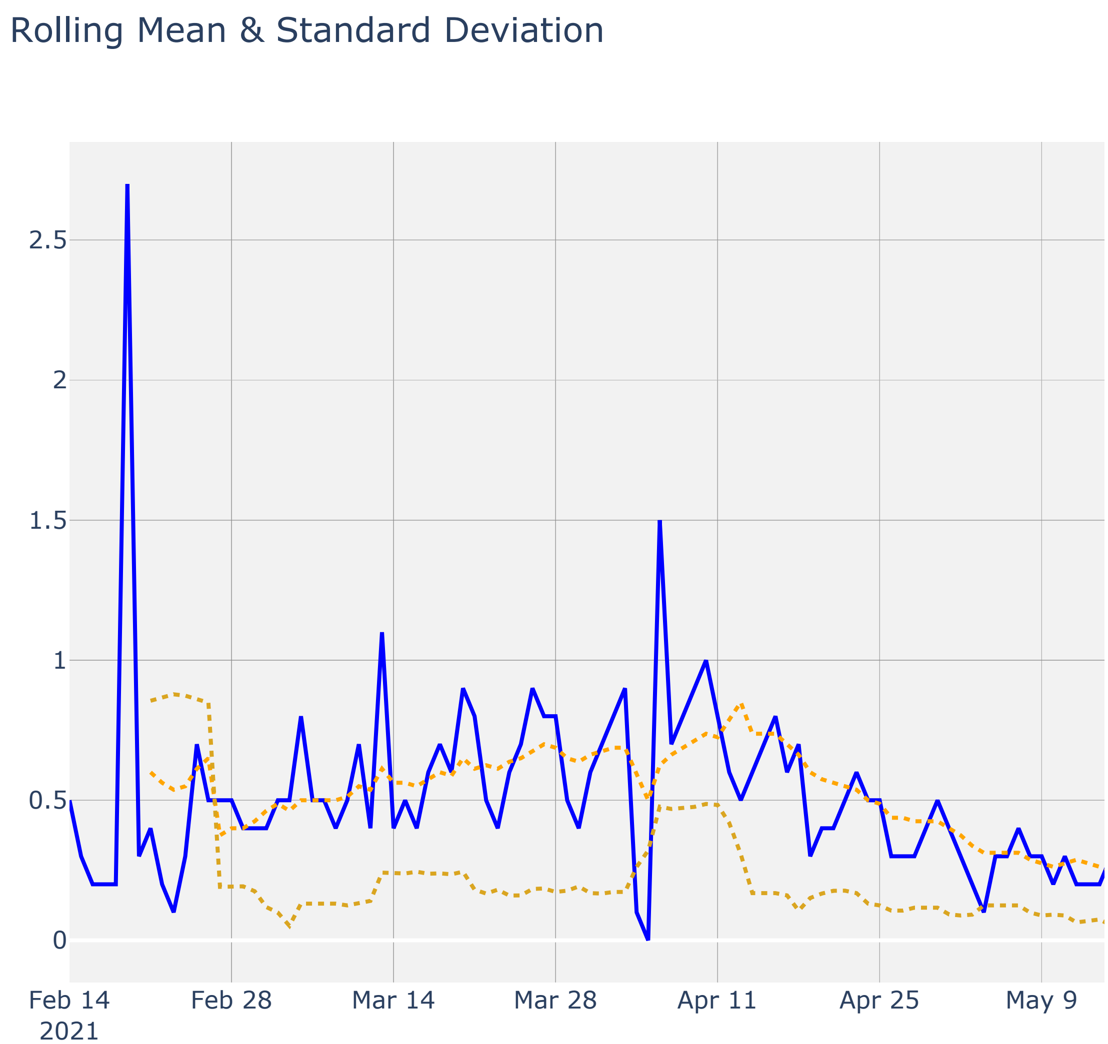
Out[29]:

	Test Stat	p-value	k-lags	n-observations	Stationary?
AD Fuller Test	-1.493298	0.536824	7	113	False

In [30]:

```
func.stationarity_check(ts1_national.diff().dropna())
```

	Test Stat	p-value	k-lags	n-observations	Stationary?
AD Fuller Test	-0.961288	0.76712	6	113	False



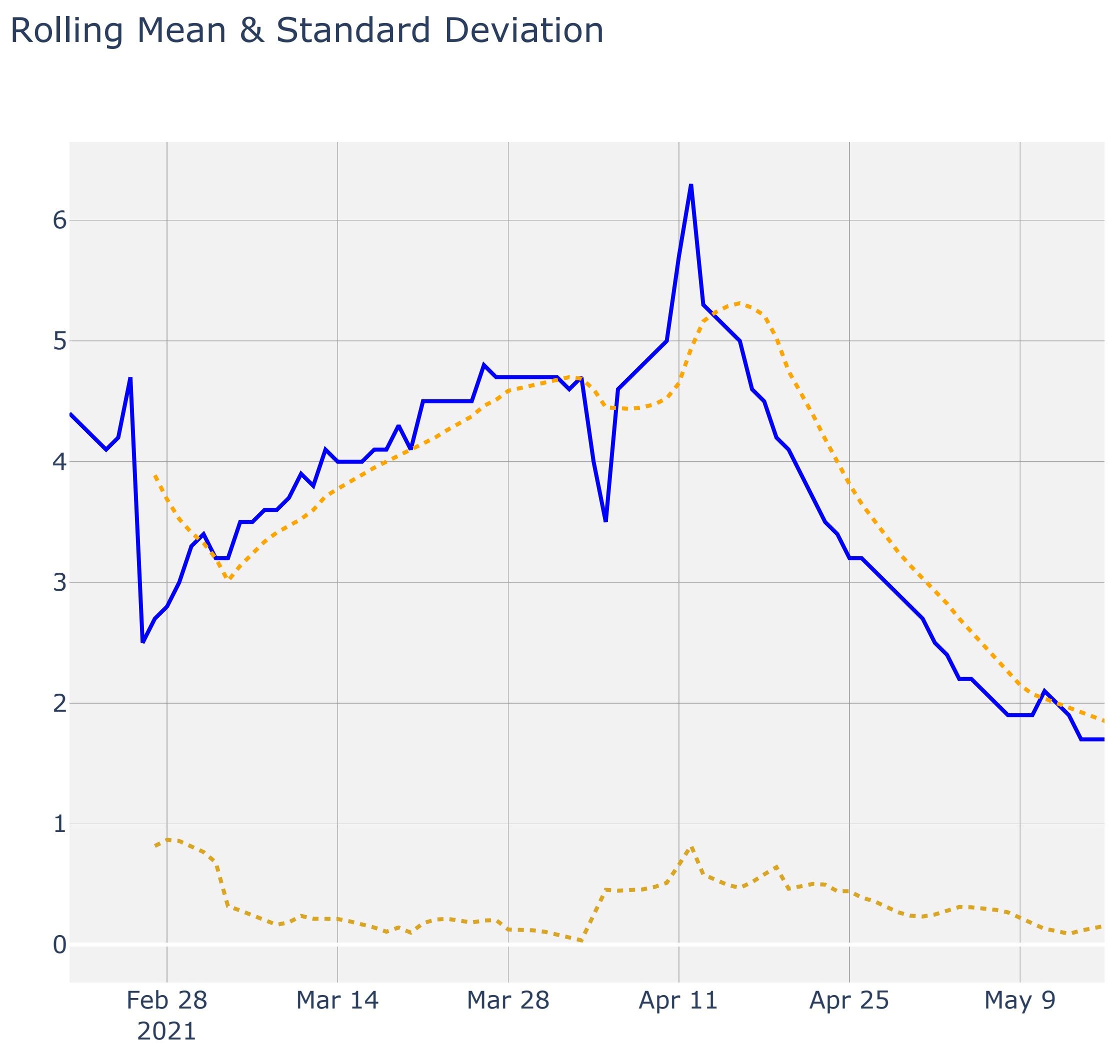
Out[30]:

	Test Stat	p-value	k-lags	n-observations	Stationary?
AD Fuller Test	-0.961288	0.76712	6	113	False

In [31]:

```
func.stationarity_check(ts1_national.diff(periods=7).dropna())
```

	Test Stat	p-value	k-lags	n-observations	Stationary?
AD Fuller Test	-0.097104	0.949726	7	106	False



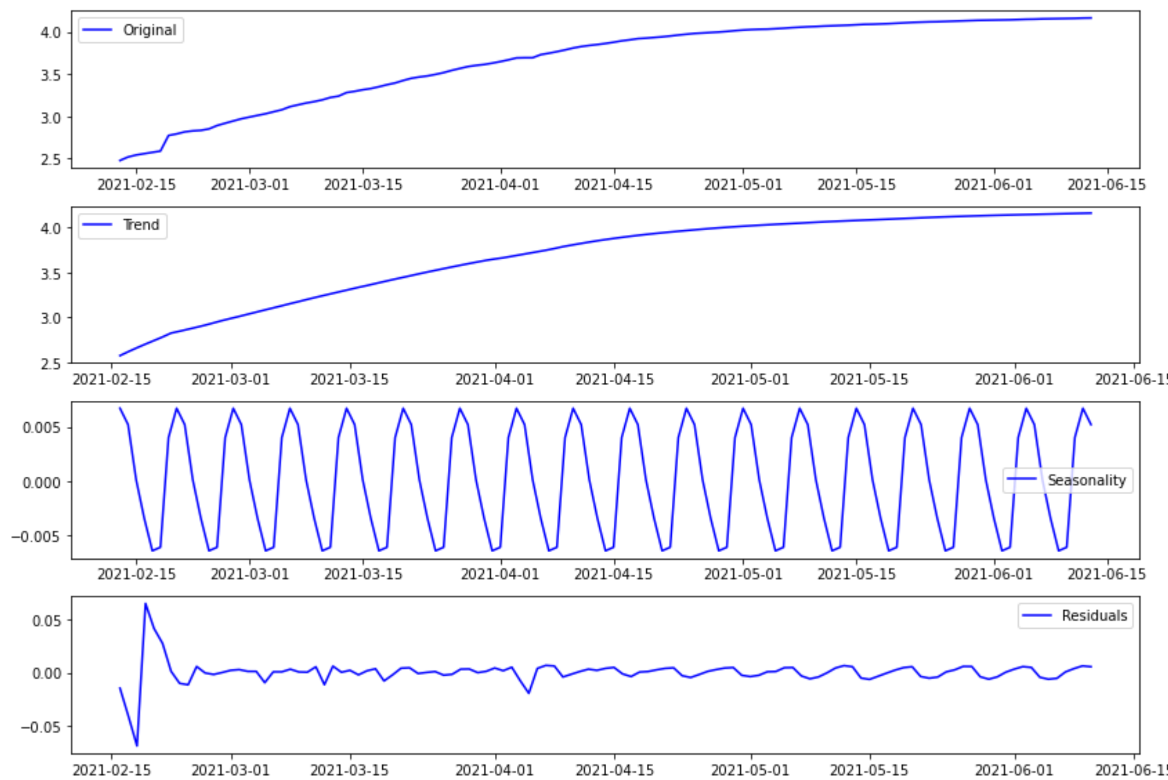
Out[31]:

	Test Stat	p-value	k-lags	n-observations	Stationary?
AD Fuller Test	-0.097104	0.949726	7	106	False

In [32]:

```
#decompose timeseries
from statsmodels.tsa.seasonal import seasonal_decompose
decomposition = seasonal_decompose(np.log(ts1_national))
trend = decomposition.trend.dropna()
seasonal = decomposition.seasonal.dropna()
residual = decomposition.resid.dropna()
```

In [33]:
```
# visualize trend, seasonality, and residuals
plt.figure(figsize=(12,8))
plt.subplot(411)
plt.plot(np.log(ts1_national), label='Original', color='blue')
plt.legend(loc='best')
plt.subplot(412)
plt.plot(trend, label='Trend', color='blue')
plt.legend(loc='best')
plt.subplot(413)
plt.plot(seasonal,label='Seasonality', color='blue')
plt.legend(loc='best')
plt.subplot(414)
plt.plot(residual, label='Residuals', color='blue')
plt.legend(loc='best')
plt.tight_layout()
```

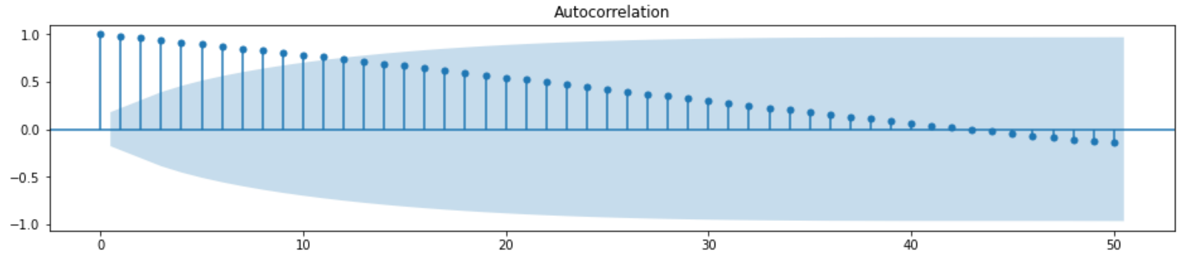


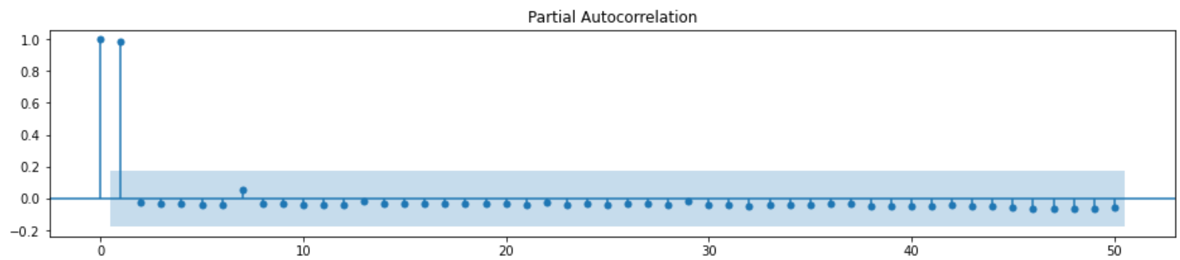
There is definitely seasonality in the data which appears to be weekly. This can be interpreted as - day of the week matters!

Explore Autocorrelation & Partial Autocorrelation

In [34]:

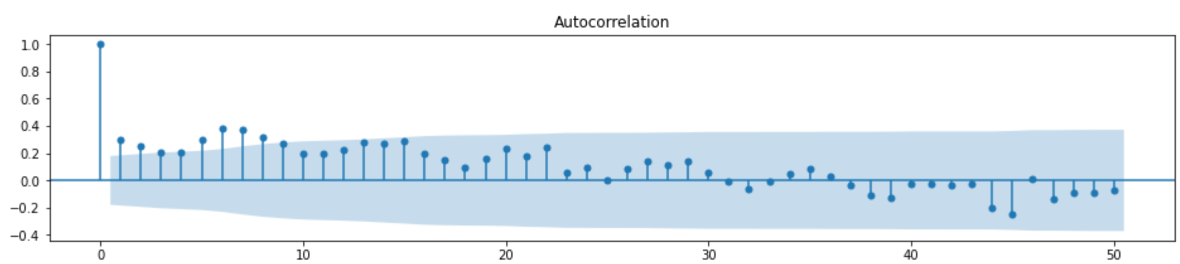
```
# regular data
func.acf_pacf_plot(ts1_national)
```

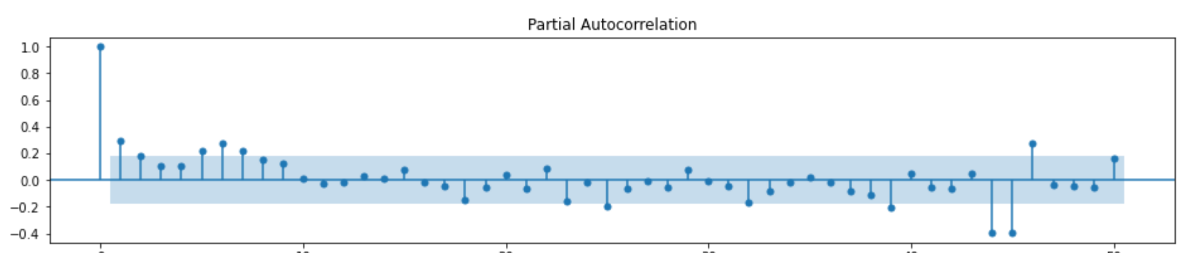




In [35]:

```
# differenced data
func.acf_pacf_plot(ts1_national.diff().dropna())
```





The partial autocorrelation plot shows a sharp drop off after one lag, suggesting an autoregressive (AR) k=1 model.

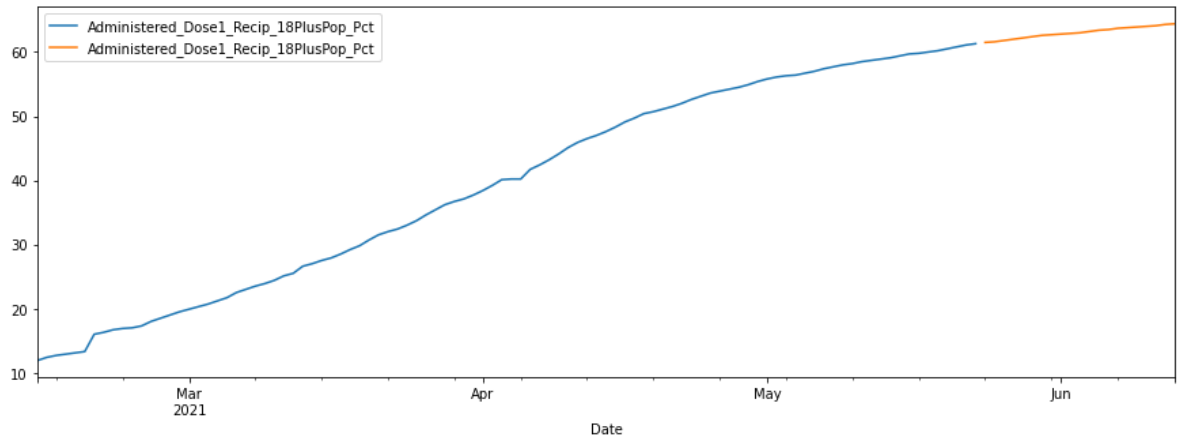
Train Test Split

In [36]:
```
# calculate how far into the future I need to forecast, to determine te
pd.to_datetime('2021-07-04') - pd.to_datetime('2021-06-13')
```

Out[36]:
```
Timedelta('21 days 00:00:00')
```

In [37]:
```
#ensure no overlap between train and test sets
ts1_national_train = ts1_national.iloc[:-21]
ts1_national_test = ts1_national.iloc[-21:]

fig, ax = plt.subplots()
ts1_national_train.plot(ax=ax, label='train')
ts1_national_test.plot(ax=ax, label='test')
```

Out[37]:
```
<AxesSubplot:xlabel='Date'>
```



Seasonal Model

Because there was some seasonal variation based on day of the week, the first model will try a season term of 7. To select the autoregressive, difference, and moving average terms, I will conduct a grid search that maximizes AIC.

Tune Parameters

In [38]:
```
#ignore convergence warnings that appear during grid search
import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning
warnings.simplefilter('ignore', ConvergenceWarning)
```

In [39]:
```
func.grid_search_pdqs(ts1_national_train, max_range=2, s=7);
```

	order	seasonal order	AIC
57	(1, 1, 1)	(0, 0, 1, 7)	-19.751433
60	(1, 1, 1)	(1, 0, 0, 7)	-18.391198
61	(1, 1, 1)	(1, 0, 1, 7)	-18.032572
63	(1, 1, 1)	(1, 1, 1, 7)	-13.418586
47	(1, 0, 1)	(1, 1, 1, 7)	-0.281454
...	...	...	...
2	(0, 0, 0)	(0, 1, 0, 7)	505.749303
9	(0, 0, 1)	(0, 0, 1, 7)	734.971341
1	(0, 0, 0)	(0, 0, 1, 7)	858.762417
8	(0, 0, 1)	(0, 0, 0, 7)	887.555781
0	(0, 0, 0)	(0, 0, 0, 7)	1025.125724

64 rows × 3 columns

Model Summary

In [40]:
```
# fit a model using optimal parameters calculated by grid search
national_model_seasonal = tsa.SARIMAX(ts1_national_train,
                              order=(1,1,1),
                              seasonal_order=(0,0,1,7),
                              enforce_invertibility=False,
                              enforce_stationarity=False).fit()
national_model_seasonal.summary()
```

Out[40]:

SARIMAX Results

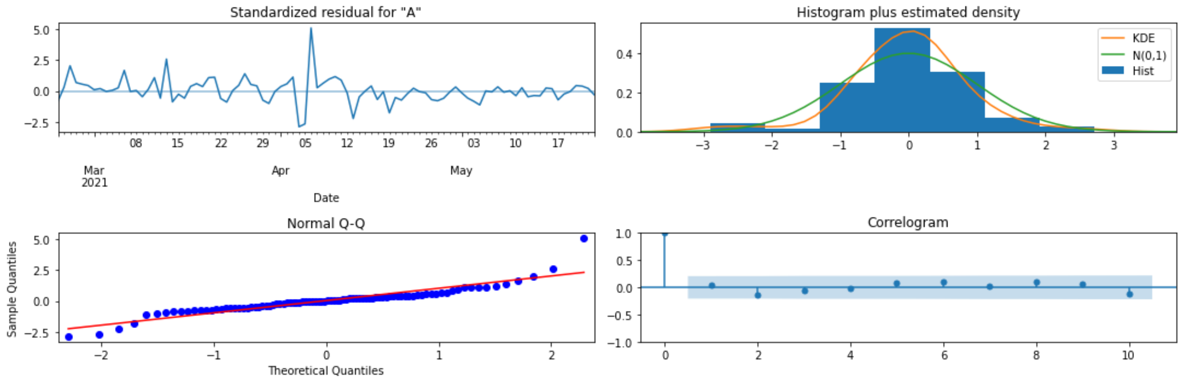
Dep. Variable:	Administered_Dose1_Recip_18PlusPop_Pct	**No. Observations:**	100
Model:	SARIMAX(1, 1, 1)x(0, 0, 1, 7)	**Log Likelihood**	13.876
Date:	Sat, 19 Jun 2021	**AIC**	-19.751
Time:	16:43:21	**BIC**	-9.752
Sample:	02-13-2021	**HQIC**	-15.719
	- 05-23-2021		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.9952	0.009	116.410	0.000	0.978	1.012
ma.L1	-0.8357	0.074	-11.326	0.000	-0.980	-0.691
ma.S.L7	0.2213	0.088	2.516	0.012	0.049	0.394
sigma2	0.0426	0.005	9.160	0.000	0.033	0.052

Ljung-Box (L1) (Q):	0.17	**Jarque-Bera (JB):**	217.17
Prob(Q):	0.68	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.26	**Skew:**	1.11
Prob(H) (two-sided):	0.00	**Kurtosis:**	10.28

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

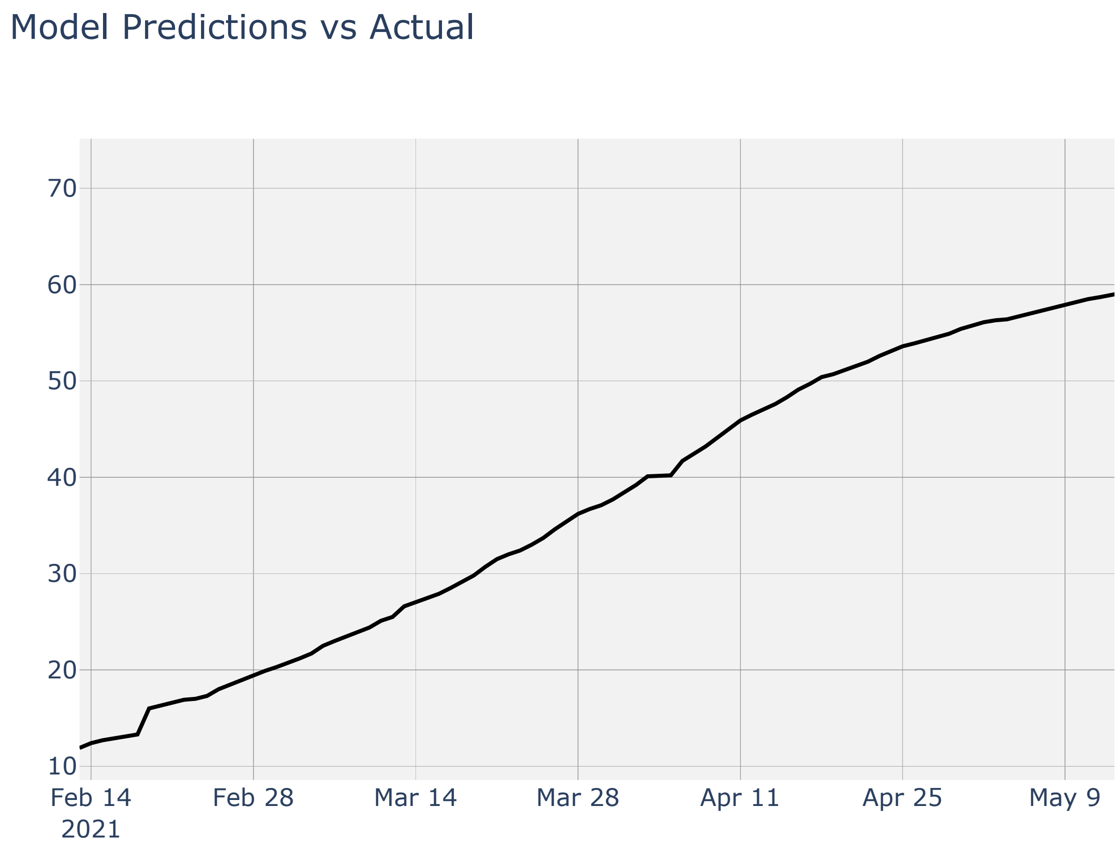
In [41]:
```
# review diagnostics
national_model_seasonal.plot_diagnostics()
plt.tight_layout();
```



Diagnostics show this to be a good model. The residuals are randomly + normally distributed, and the correlogram mirrors that of a white noise model.

Validate

In [42]:
```
# plot the predictions against the actual observations
func.validate_model(national_model_seasonal, ts1_national)
```



Out[42]:

	lower	upper	predictions
2021-05-24	61.105303	61.914438	61.509871
2021-05-25	61.115609	62.354482	61.735046
2021-05-26	61.148954	62.783663	61.966309
2021-05-27	61.206320	63.230814	62.218567
2021-05-28	61.261985	63.679570	62.470777
2021-05-29	61.307274	64.125294	62.716284
2021-05-30	61.325093	64.552821	62.938957
2021-05-31	61.304564	65.038997	63.171781
2021-06-01	61.277865	65.529086	63.403475
2021-06-02	61.244348	66.023745	63.634047
2021-06-03	61.203692	66.523307	63.863499
2021-06-04	61.155759	67.027920	64.091839
2021-06-05	61.100519	67.537625	64.319072
2021-06-06	61.038012	68.052394	64.545203

	lower	upper	predictions
2021-06-07	60.968315	68.572158	64.770237
2021-06-08	60.891533	69.096826	64.994179
2021-06-09	60.807785	69.626286	65.217035
2021-06-10	60.717199	70.160423	65.438811
2021-06-11	60.619908	70.699114	65.659511
2021-06-12	60.516047	71.242234	65.879141
2021-06-13	60.405750	71.789661	66.097705

This is a good model; the predictions are slightly higher than the actual observations, but well inside the upper confidence interval.

I will try a non-seasonal model next just to see if it performs any better.

ARIMA Model

Tune Parameters

In [43]:

```
#grid search optimal order parameter for an ARIMA model
func.grid_search_pdq(ts1_national_train, max_range=3)
```

	order	AIC
17	(1, 2, 2)	56.693502
19	(2, 0, 1)	57.699503
23	(2, 1, 2)	57.897565
26	(2, 2, 2)	59.155321
7	(0, 2, 1)	60.056808
13	(1, 1, 1)	61.411930
16	(1, 2, 1)	62.744920
8	(0, 2, 2)	62.848859
20	(2, 0, 2)	62.988448
9	(1, 0, 0)	63.298308
22	(2, 1, 1)	63.411944
14	(1, 1, 2)	63.954007
25	(2, 2, 1)	64.104590
10	(1, 0, 1)	64.495397
11	(1, 0, 2)	66.007701
24	(2, 2, 0)	87.524335
21	(2, 1, 0)	90.483096
15	(1, 2, 0)	93.990295
12	(1, 1, 0)	104.553456
18	(2, 0, 0)	107.979273
6	(0, 2, 0)	116.077828
5	(0, 1, 2)	126.381764
4	(0, 1, 1)	142.873726
3	(0, 1, 0)	180.461218
2	(0, 0, 2)	572.963322
1	(0, 0, 1)	693.530221
0	(0, 0, 0)	830.724187

Out[43]:

	order	AIC
17	(1, 2, 2)	56.693502
19	(2, 0, 1)	57.699503
23	(2, 1, 2)	57.897565

	order	AIC
26	(2, 2, 2)	59.155321
7	(0, 2, 1)	60.056808
13	(1, 1, 1)	61.411930
16	(1, 2, 1)	62.744920
8	(0, 2, 2)	62.848859
20	(2, 0, 2)	62.988448
9	(1, 0, 0)	63.298308
22	(2, 1, 1)	63.411944
14	(1, 1, 2)	63.954007
25	(2, 2, 1)	64.104590
10	(1, 0, 1)	64.495397
11	(1, 0, 2)	66.007701
24	(2, 2, 0)	87.524335
21	(2, 1, 0)	90.483096
15	(1, 2, 0)	93.990295
12	(1, 1, 0)	104.553456
18	(2, 0, 0)	107.979273
6	(0, 2, 0)	116.077828
5	(0, 1, 2)	126.381764
4	(0, 1, 1)	142.873726
3	(0, 1, 0)	180.461218
2	(0, 0, 2)	572.963322
1	(0, 0, 1)	693.530221
0	(0, 0, 0)	830.724187

Model Summary

In [44]:

```
#fit the model using optimal order parameter found
national_model = tsa.arima.ARIMA(ts1_national_train,
                                 order=(1,2,2),
                                 enforce_invertibility=False,
                                 enforce_stationarity=False).fit()
national_model.summary()
```

Out[44]:

SARIMAX Results

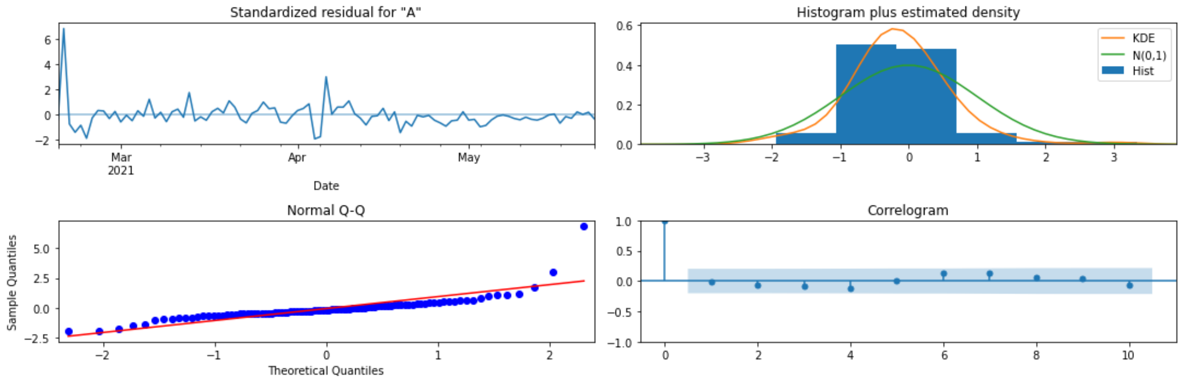
Dep. Variable:	Administered_Dose1_Recip_18PlusPop_Pct	**No. Observations:**	100
Model:	ARIMA(1, 2, 2)	**Log Likelihood**	-24.347
Date:	Sat, 19 Jun 2021	**AIC**	56.694
Time:	16:43:23	**BIC**	66.909
Sample:	02-13-2021	**HQIC**	60.821
	- 05-23-2021		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.9123	0.046	-19.797	0.000	-1.003	-0.822
ma.L1	0.1073	142.064	0.001	0.999	-278.333	278.547
ma.L2	-0.8927	126.809	-0.007	0.994	-249.433	247.648
sigma2	0.0940	13.352	0.007	0.994	-26.075	26.263

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	2266.69
Prob(Q):	0.93	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.09	**Skew:**	3.65
Prob(H) (two-sided):	0.00	**Kurtosis:**	25.79

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

In [45]:
```
#review diagnostics
national_model.plot_diagnostics()
plt.tight_layout();
```

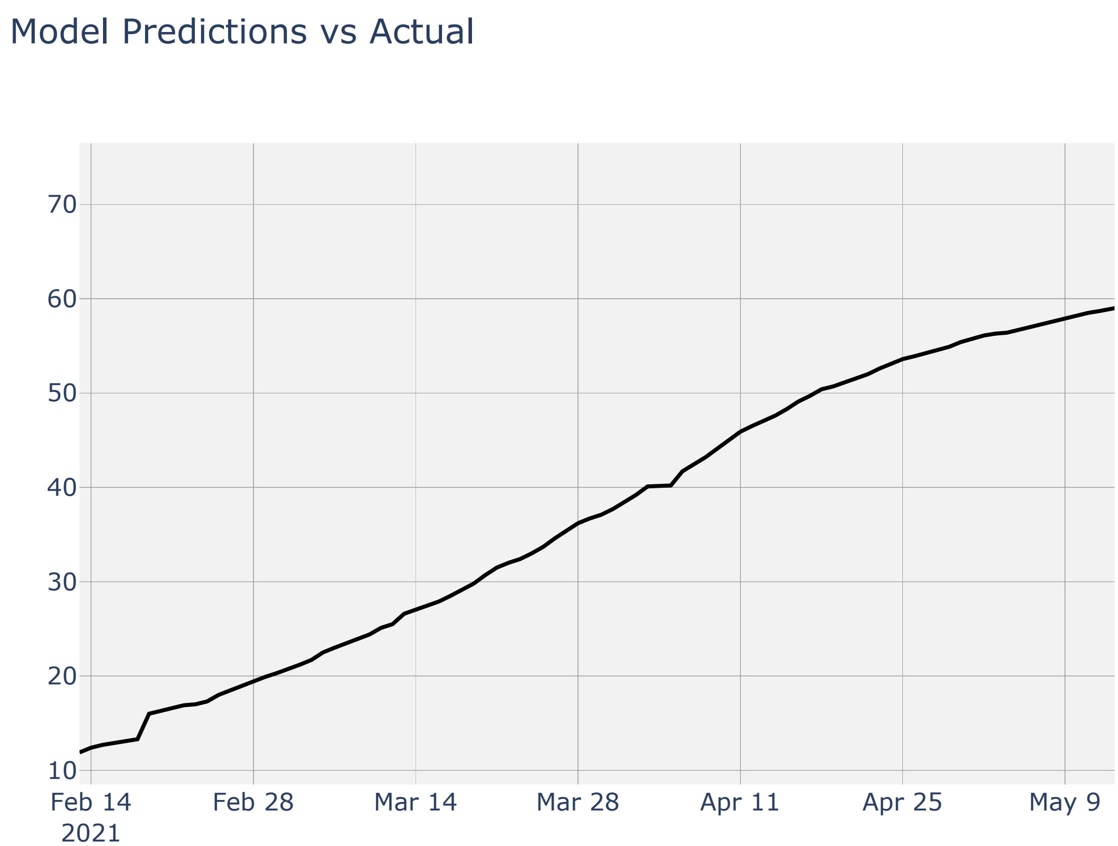


No red flags appear here; this seems to be a good model too.

Validate

In [46]:

```
func.validate_model(national_model, ts1_national)
```



Out[46]:

	lower	upper	predictions
2021-05-24	60.927411	62.135217	61.531314
2021-05-25	60.887529	62.760250	61.823890
2021-05-26	60.865444	63.255705	62.060574
2021-05-27	60.883445	63.813055	62.348250
2021-05-28	60.880179	64.298631	62.589405
2021-05-29	60.903312	64.842693	62.873002
2021-05-30	60.900500	65.335256	63.117878
2021-05-31	60.917795	65.878367	63.398081
2021-06-01	60.909815	66.382292	63.646054
2021-06-02	60.917606	66.929256	63.923431
2021-06-03	60.902147	67.445817	64.173982
2021-06-04	60.899069	67.998945	64.449007
2021-06-05	60.875057	68.528349	64.701703
2021-06-06	60.860663	69.088879	64.974771

	lower	upper	predictions
2021-06-07	60.827582	69.630925	65.229254
2021-06-08	60.801831	70.199553	65.500692
2021-06-09	60.759448	70.753874	65.756661
2021-06-10	60.722489	71.330996	66.026743
2021-06-11	60.670726	71.897173	66.283949
2021-06-12	60.622800	72.483005	66.552902
2021-06-13	60.561666	73.060611	66.811138

The non-seasonal model also performs well, and the naked eye can't decipher which is better. The primary way to mathematically confirm which model is better is by finding the lower AIC value.

In [47]:

```
#compare AIC values
print(f'Non-Seasonal Model AIC: {national_model.aic}')
print(f'Seasonal Model AIC: {national_model_seasonal.aic}')
```

```
Non-Seasonal Model AIC: 56.693501577226854
Seasonal Model AIC: -19.751433054509384
```

The seasonal model performed better than the non-seasonal model.

National Forecast

Now I'll use the best performing national model to forecast into the future.

In [48]:

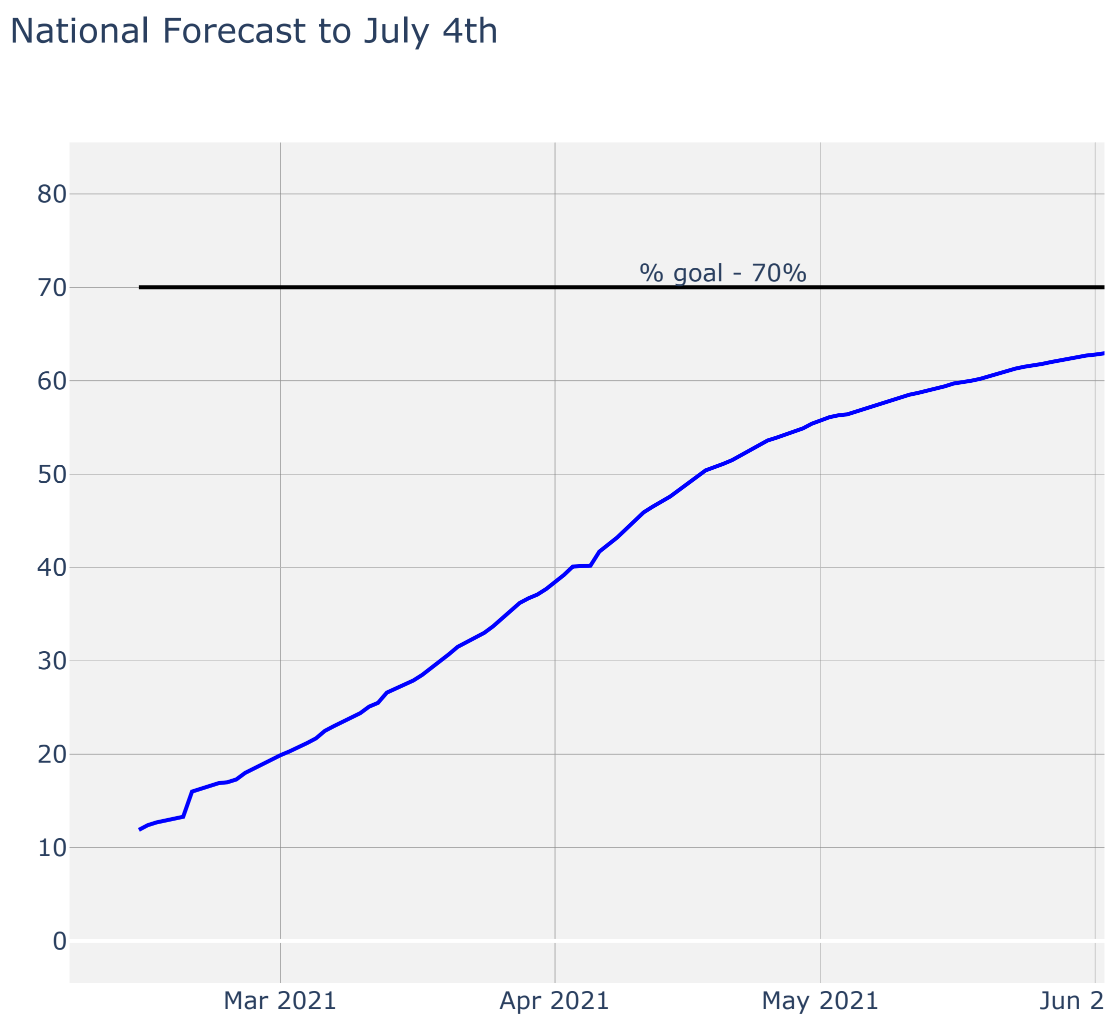
```
#review order parameters for the seasonal model
national_model_seasonal.model_orders
```

Out[48]:

```
{'trend': 0,
 'exog': 0,
 'ar': 1,
 'ma': 1,
 'seasonal_ar': 0,
 'seasonal_ma': 7,
 'reduced_ar': 1,
 'reduced_ma': 8,
 'exog_variance': 0,
 'measurement_variance': 0,
 'variance': 1}
```

In [49]:
```
#fit a model on the full dataset using optimal order parameters for SA
national_model_full = tsa.arima.ARIMA(ts1_national,
                                     order=(1,1,1),
                                     seasonal_order=(0,0,1,7),
                                     enforce_invertibility=False,
                                     enforce_stationarity=False).fit(

func.plot_forecast(national_model_full, ts1_national, steps=21, title=
                   file_name='national_forecast_20210704')
```

```
Forecast for 7/4/21: 66.95849456591688
```



The model forecasts that 66.96% of the adult population will have received at least one vaccine dose by July 4th, coming short of the 70% goal. However, the goal is within the upper confidence interval.

Upper confidence interval: 72.93%

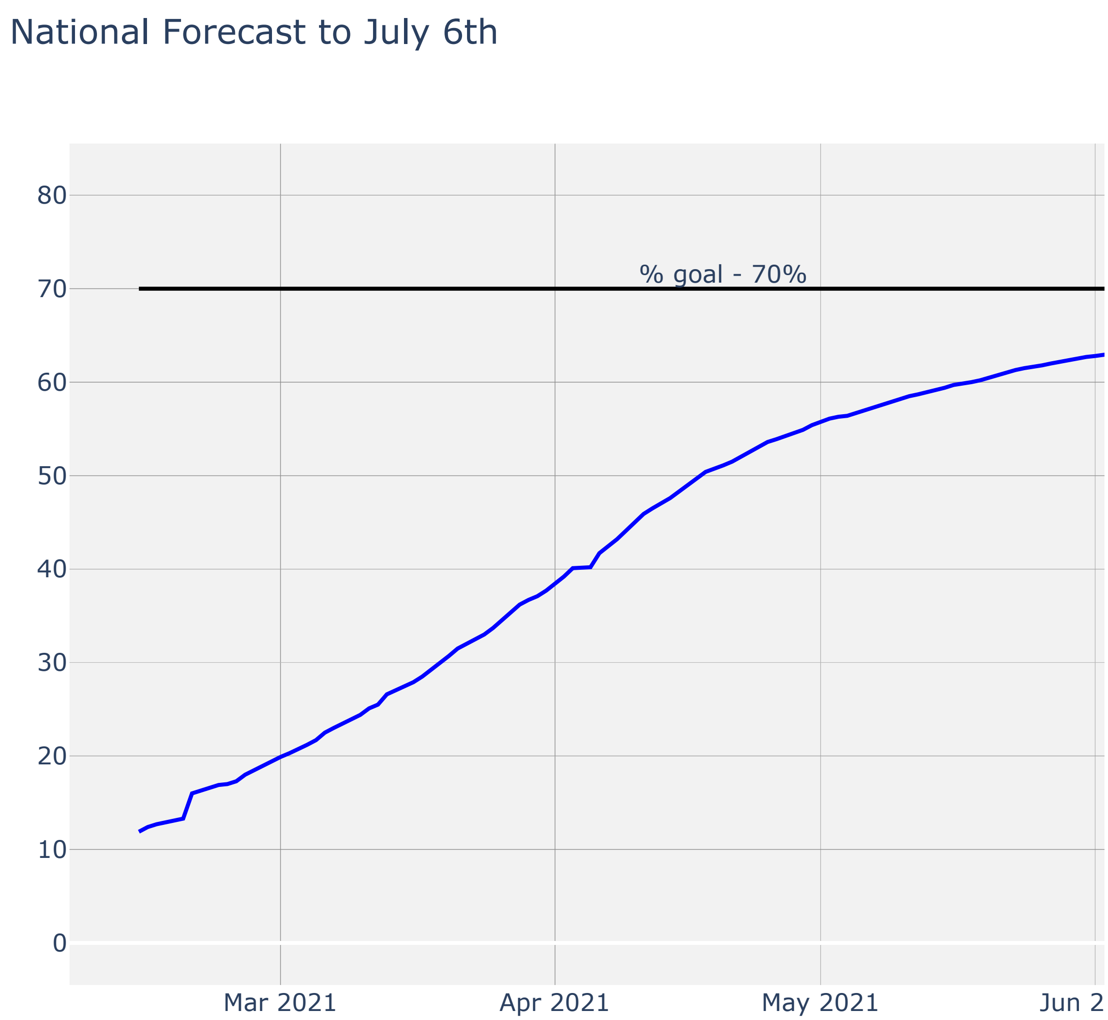
Forecast: 66.96%

Lower confidence interval: 61.78%

Because the data source mentions a 48 hour lag in reporting data, I want to see what the forecast through July 6th - two days past the deadline - would be.

In [50]:
```
#increase step size by 2 extra days
func.plot_forecast(national_model_full, ts1_national, steps=23, title='
                   file_name='national_forecast_20210706')
```

```
Forecast for 7/4/21: 66.95849456591688
```



This lag is not projected to be very meaningful, gaining 0.22 percentage points in two days but still forecasting 67.19%, which is lower than the 70% goal.

Regional Analysis

Regional Analysis

As observed early, trends vary significantly by region of the US. It may be helpful to target campaigns in the final weeks leading up to July 4th in the regions that have lower administration rates.

Let's see which region(s) need additional support.

In [51]:

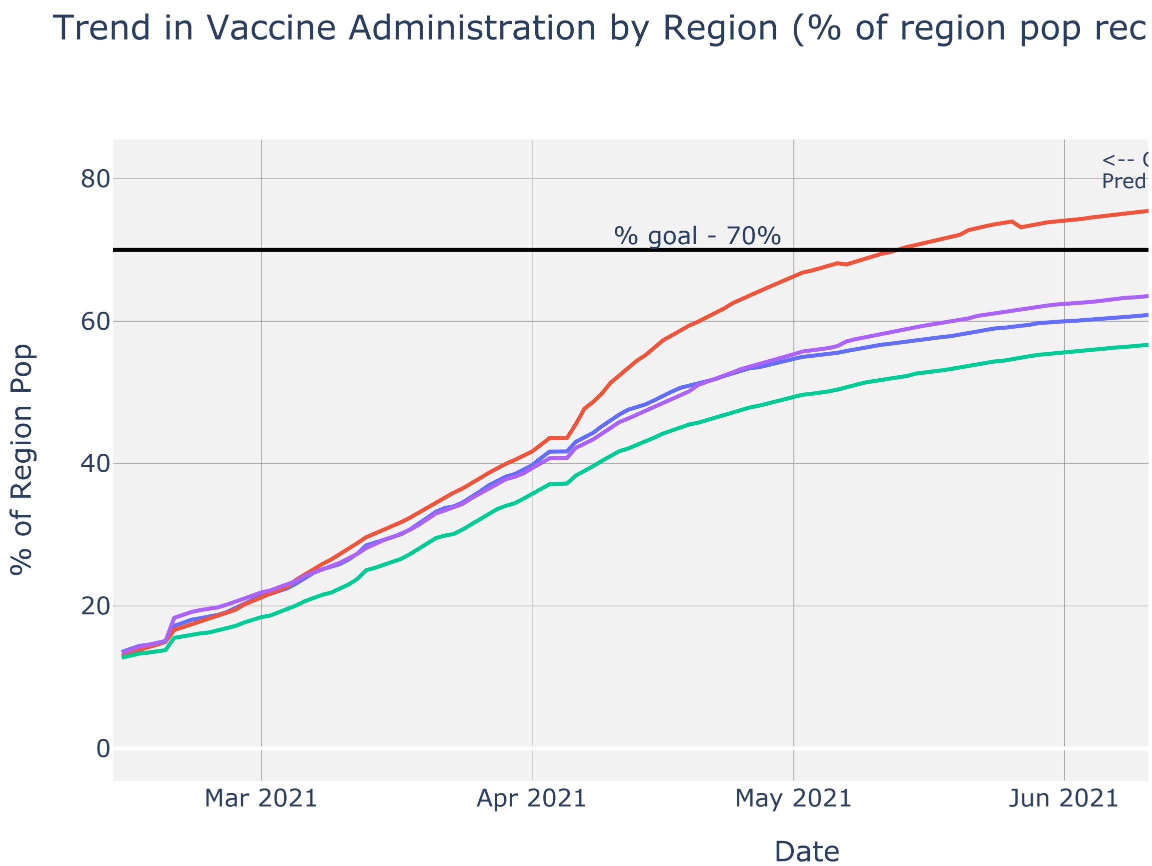
```
ts1_region
```

Out[51]:

	Region	Administered_Dose1_Recip_18PlusPop_Pct
Date		
2021-02-13	Midwest	13.550000
2021-02-13	Northeast	12.944444
2021-02-13	South	12.747059
2021-02-13	West	13.400000
2021-02-14	Midwest	14.075000
...	...	...
2021-06-12	West	63.700000
2021-06-13	Midwest	61.058333
2021-06-13	Northeast	75.822222
2021-06-13	South	56.944444
2021-06-13	West	63.800000

484 rows × 2 columns

In [52]:
```
func.plot_vax(ts1_region, color='Region',
              title="Trend in Vaccine Administration by Region (% of re
              labels={'value': '% of Region Pop'})
```



The northeast is leading the nation, meeting the 70% goal in mid-May and reporting nearly 80% of the adult population having received at least one vaccine dose as of June 13.

The west (63.8%), midwest (61.1%), and south (57.0%) trail quite significantly, though it appears the west is on the strongest upward trajectory of the three regions.

In the following cells, the 3 lagging regions will each be modeled to forecast what percentage they will reach by July 4th.

West

Preprocessing

In [53]:
```
# create df, drop unused feature, and resample
ts1_west = ts1_region[ts1_region.Region == 'West']
ts1_west = ts1_west.drop(columns='Region')
ts1_west = ts1_west.resample('D').asfreq()
display(ts1_west)
ts1_west.index
```

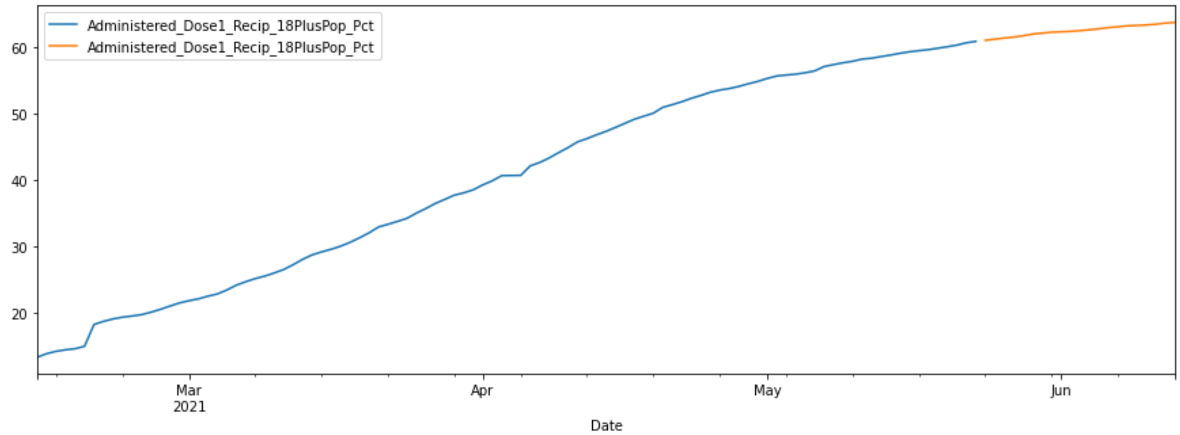
	Administered_Dose1_Recip_18PlusPop_Pct
Date	
2021-02-13	13.400000
2021-02-14	13.938462
2021-02-15	14.292308
2021-02-16	14.523077
2021-02-17	14.684615
...	...
2021-06-09	63.338462
2021-06-10	63.407692
2021-06-11	63.523077
2021-06-12	63.700000
2021-06-13	63.800000

121 rows × 1 columns

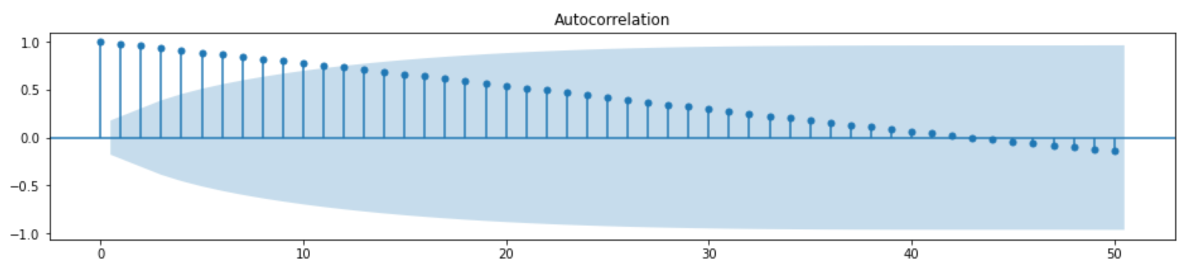
Out[53]:
```
DatetimeIndex(['2021-02-13', '2021-02-14', '2021-02-15', '2021-02-16',
               '2021-02-17', '2021-02-18', '2021-02-19', '2021-02-20',
               '2021-02-21', '2021-02-22',
               ...
               '2021-06-04', '2021-06-05', '2021-06-06', '2021-06-07',
               '2021-06-08', '2021-06-09', '2021-06-10', '2021-06-11',
               '2021-06-12', '2021-06-13'],
              dtype='datetime64[ns]', name='Date', length=121, freq='D
```

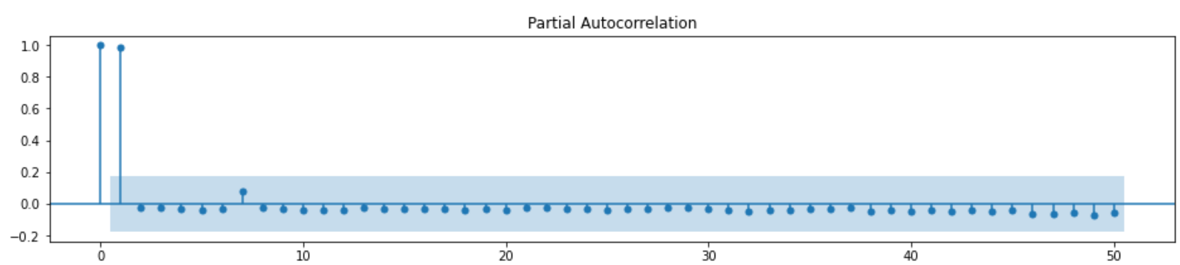
In [54]:
```
#train test split
ts1_west_train = ts1_west.iloc[:-21]
ts1_west_test = ts1_west.iloc[-21:]

#ensure no overlap between train and test sets
fig, ax = plt.subplots()
ts1_west_train.plot(ax=ax, label='train')
ts1_west_test.plot(ax=ax, label='test')
```

Out[54]:
```
<AxesSubplot:xlabel='Date'>
```

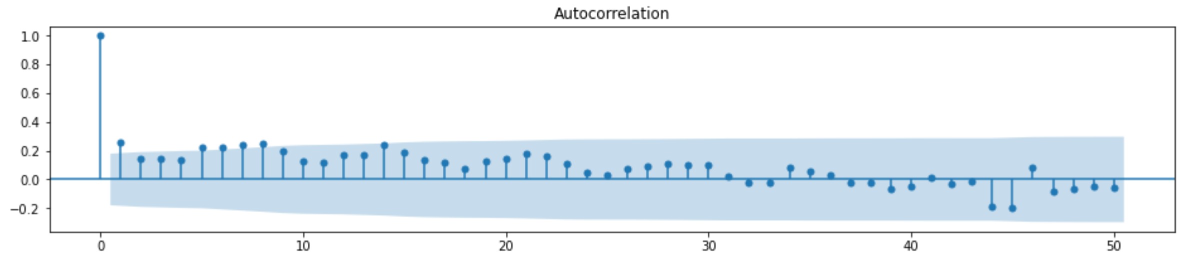


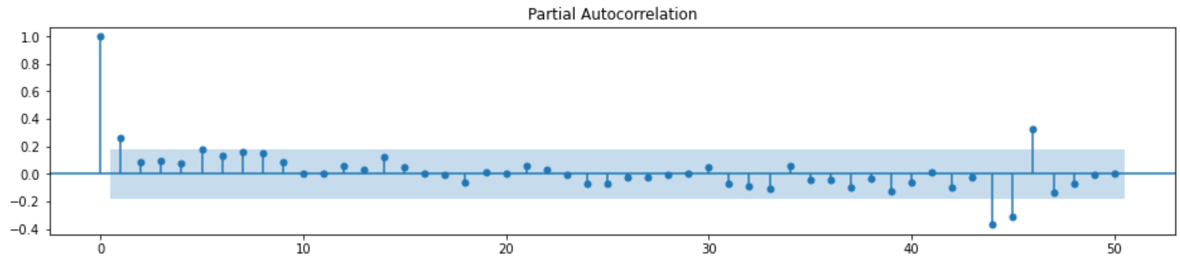
In [55]:
```
func.acf_pacf_plot(ts1_west)
```





In [56]:
```
func.acf_pacf_plot(ts1_west.diff().dropna())
```





The west region closely mirrors the national trends, exhibiting some seasonality related to day of the week.

Seasonal Model

In [57]:
```
# grid search optimal order parameters
func.grid_search_pdqs(ts1_west_train, max_range=3, s=7);
```

	order	seasonal order	AIC
370	(1, 1, 1)	(2, 0, 1, 7)	-33.873496
362	(1, 1, 1)	(1, 0, 2, 7)	-32.790325
198	(0, 2, 1)	(1, 0, 0, 7)	-32.660155
397	(1, 1, 2)	(2, 0, 1, 7)	-32.233883
371	(1, 1, 1)	(2, 0, 2, 7)	-31.297895
...	...	...	...
2	(0, 0, 0)	(0, 0, 2, 7)	805.025460
1	(0, 0, 0)	(0, 0, 1, 7)	859.944296
27	(0, 0, 1)	(0, 0, 0, 7)	888.967905
28	(0, 0, 1)	(0, 0, 1, 7)	962.227438
0	(0, 0, 0)	(0, 0, 0, 7)	1026.584528

729 rows × 3 columns

In [58]:

```
# fit the training set using optimal orders found
west_model_s = tsa.SARIMAX(ts1_west_train,
                           order=(1,1,1),
                           seasonal_order=(2,0,1,7),
                           enforce_invertibility=False,
                           enforce_stationarity=False).fit()
west_model_s.summary()
```

Out[58]:

SARIMAX Results

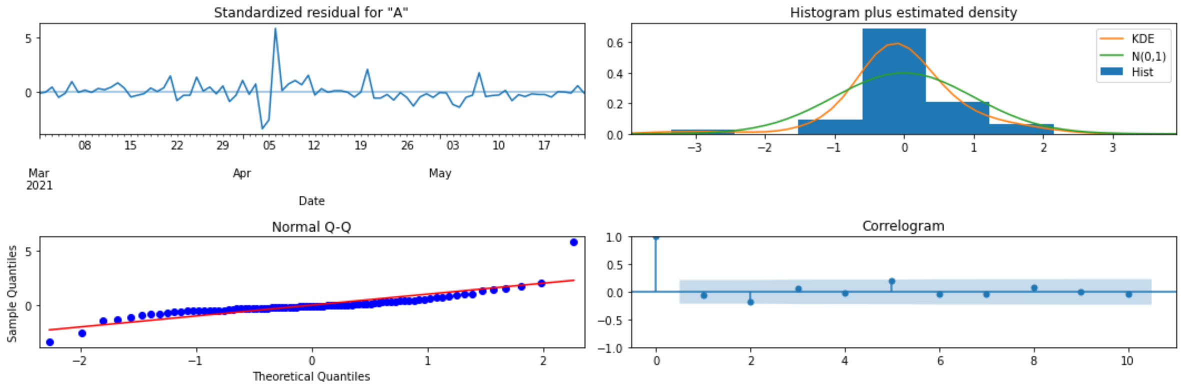
Dep. Variable:	Administered_Dose1_Recip_18PlusPop_Pct	**No. Observations:**	100
Model:	SARIMAX(1, 1, 1)x(2, 0, 1, 7)	**Log Likelihood**	22.937
Date:	Sat, 19 Jun 2021	**AIC**	-33.873
Time:	16:46:52	**BIC**	-19.289
Sample:	02-13-2021	**HQIC**	-28.010
	- 05-23-2021		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.9664	0.024	40.163	0.000	0.919	1.014
ma.L1	-0.8867	0.068	-13.081	0.000	-1.020	-0.754
ar.S.L7	0.7794	0.182	4.274	0.000	0.422	1.137
ar.S.L14	0.0467	0.106	0.439	0.661	-0.162	0.255
ma.S.L7	-0.7718	0.153	-5.059	0.000	-1.071	-0.473
sigma2	0.0306	0.004	8.413	0.000	0.023	0.038

Ljung-Box (L1) (Q):	0.24	**Jarque-Bera (JB):**	653.45
Prob(Q):	0.63	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.31	**Skew:**	1.86
Prob(H) (two-sided):	0.48	**Kurtosis:**	16.15

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

In [59]:
```
#review diagnostics
west_model_s.plot_diagnostics();
plt.tight_layout()
```



No red flags, but since the ACF/PACF showed less seasonality in the west, let's test an ARIMA model to see if it performs better.

ARIMA Model

In [60]:
```
# grid search optimal order parameter
func.grid_search_pdq(ts1_west_train, max_range=3);
```

	order	AIC
17	(1, 2, 2)	75.337958
23	(2, 1, 2)	76.091562
26	(2, 2, 2)	76.429041
9	(1, 0, 0)	78.228628
10	(1, 0, 1)	79.612769
7	(0, 2, 1)	80.622944
19	(2, 0, 1)	80.657725
13	(1, 1, 1)	81.514339
11	(1, 0, 2)	82.840977
8	(0, 2, 2)	82.853584
16	(1, 2, 1)	83.147934
14	(1, 1, 2)	83.505992
22	(2, 1, 1)	84.057724
20	(2, 0, 2)	84.101598
25	(2, 2, 1)	84.326346
24	(2, 2, 0)	107.652825
21	(2, 1, 0)	110.468271
15	(1, 2, 0)	116.132593
12	(1, 1, 0)	119.103958
18	(2, 0, 0)	122.390337
6	(0, 2, 0)	133.476862
5	(0, 1, 2)	135.867735
4	(0, 1, 1)	146.467078
3	(0, 1, 0)	180.334691
2	(0, 0, 2)	559.154860
1	(0, 0, 1)	680.974491
0	(0, 0, 0)	818.145346

In [61]:

```
# fit model on training set, optimal order param found
west_model = tsa.arima.ARIMA(ts1_west_train,
                            order=(1,2,2),
                            enforce_invertibility=False,
                            enforce_stationarity=False).fit()
west_model.summary()
```

Out[61]:

SARIMAX Results

Dep. Variable:	Administered_Dose1_Recip_18PlusPop_Pct	**No. Observations:**	100
Model:	ARIMA(1, 2, 2)	**Log Likelihood**	-33.669
Date:	Sat, 19 Jun 2021	**AIC**	75.338
Time:	16:46:54	**BIC**	85.553
Sample:	02-13-2021	**HQIC**	79.466
	- 05-23-2021		
Covariance Type:	opg		

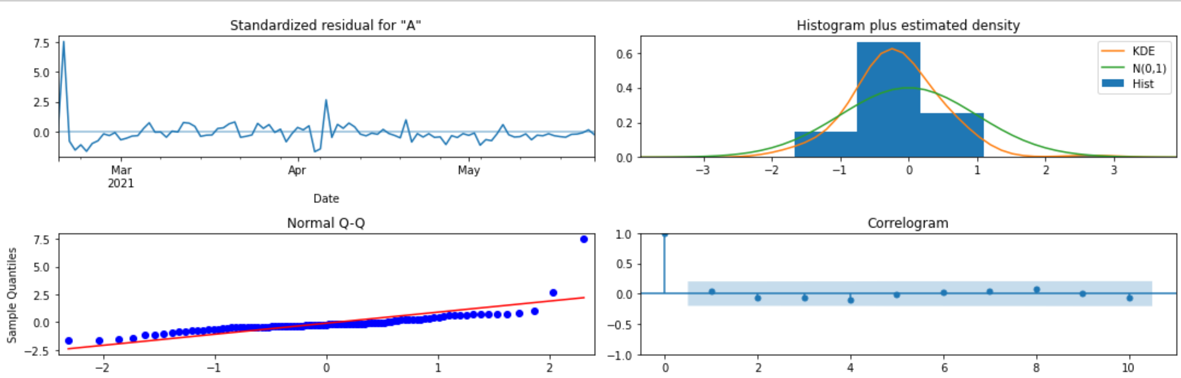
	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	-0.8755	0.052	-16.912	0.000	-0.977	-0.774
ma.L1	-0.0876	309.137	-0.000	1.000	-605.985	605.810
ma.L2	-1.0877	336.201	-0.003	0.997	-660.029	657.854
sigma2	0.0965	29.823	0.003	0.997	-58.355	58.548

Ljung-Box (L1) (Q):	0.10	**Jarque-Bera (JB):**	5001.51
Prob(Q):	0.75	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.10	**Skew:**	4.82
Prob(H) (two-sided):	0.00	**Kurtosis:**	37.21

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

In [62]:

```
#review diagnostics
west_model.plot_diagnostics();
plt.tight_layout()
```



In [63]:
```
#compare AICs
print(f'Seasonal Model AIC: {west_model_s.aic}')
print(f'Non-Seasonal Model AIC: {west_model.aic}')
```

```
Seasonal Model AIC: -33.873496195487625
Non-Seasonal Model AIC: 75.33795820729108
```

The seasonal model performed much better, so that's the one we will forecast into the future with.

Forecast

In [64]:
```
west_model_s.model_orders
```

Out[64]:
```
{'trend': 0,
 'exog': 0,
 'ar': 1,
 'ma': 1,
 'seasonal_ar': 14,
 'seasonal_ma': 7,
 'reduced_ar': 15,
 'reduced_ma': 8,
 'exog_variance': 0,
 'measurement_variance': 0,
 'variance': 1}
```

In [65]:
```
#fit the model on the full dataset, optimal order parameters for SARIM/
west_model_full = tsa.SARIMAX(ts1_west,
                              order=(1,1,1),
                              seasonal_order=(2,0,1,7),
                              enforce_invertibility=False,
                              enforce_stationarity=False).fit()
west_model_full.summary()
```

Out[65]:

SARIMAX Results

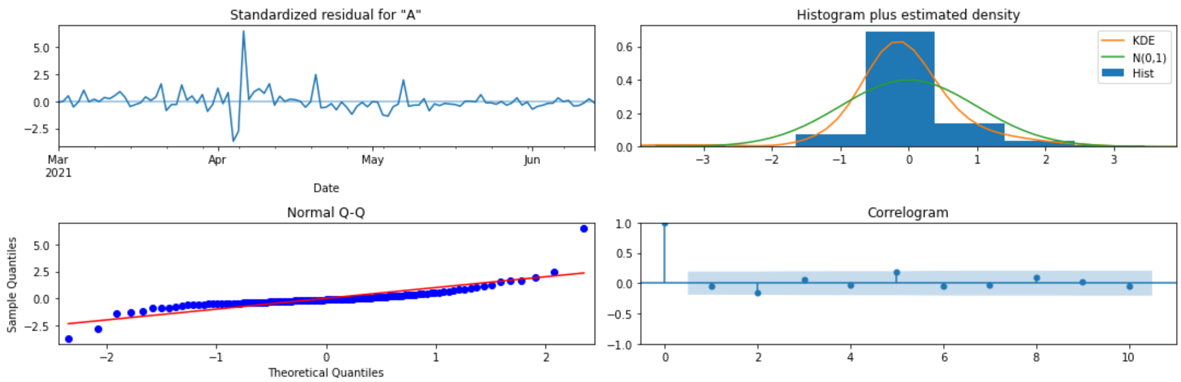
Dep. Variable:	Administered_Dose1_Recip_18PlusPop_Pct	**No. Observations:**	121
Model:	SARIMAX(1, 1, 1)x(2, 0, 1, 7)	**Log Likelihood**	40.562
Date:	Sat, 19 Jun 2021	**AIC**	-69.124
Time:	16:46:55	**BIC**	-53.200
Sample:	02-13-2021	**HQIC**	-62.672
	- 06-13-2021		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	0.9619	0.021	45.256	0.000	0.920	1.004
ma.L1	-0.8744	0.057	-15.329	0.000	-0.986	-0.763
ar.S.L7	0.7995	0.143	5.584	0.000	0.519	1.080
ar.S.L14	0.0405	0.089	0.457	0.647	-0.133	0.214
ma.S.L7	-0.8245	0.128	-6.423	0.000	-1.076	-0.573
sigma2	0.0245	0.002	10.345	0.000	0.020	0.029

Ljung-Box (L1) (Q):	0.31	**Jarque-Bera (JB):**	1401.35
Prob(Q):	0.58	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.15	**Skew:**	2.24
Prob(H) (two-sided):	0.00	**Kurtosis:**	20.33

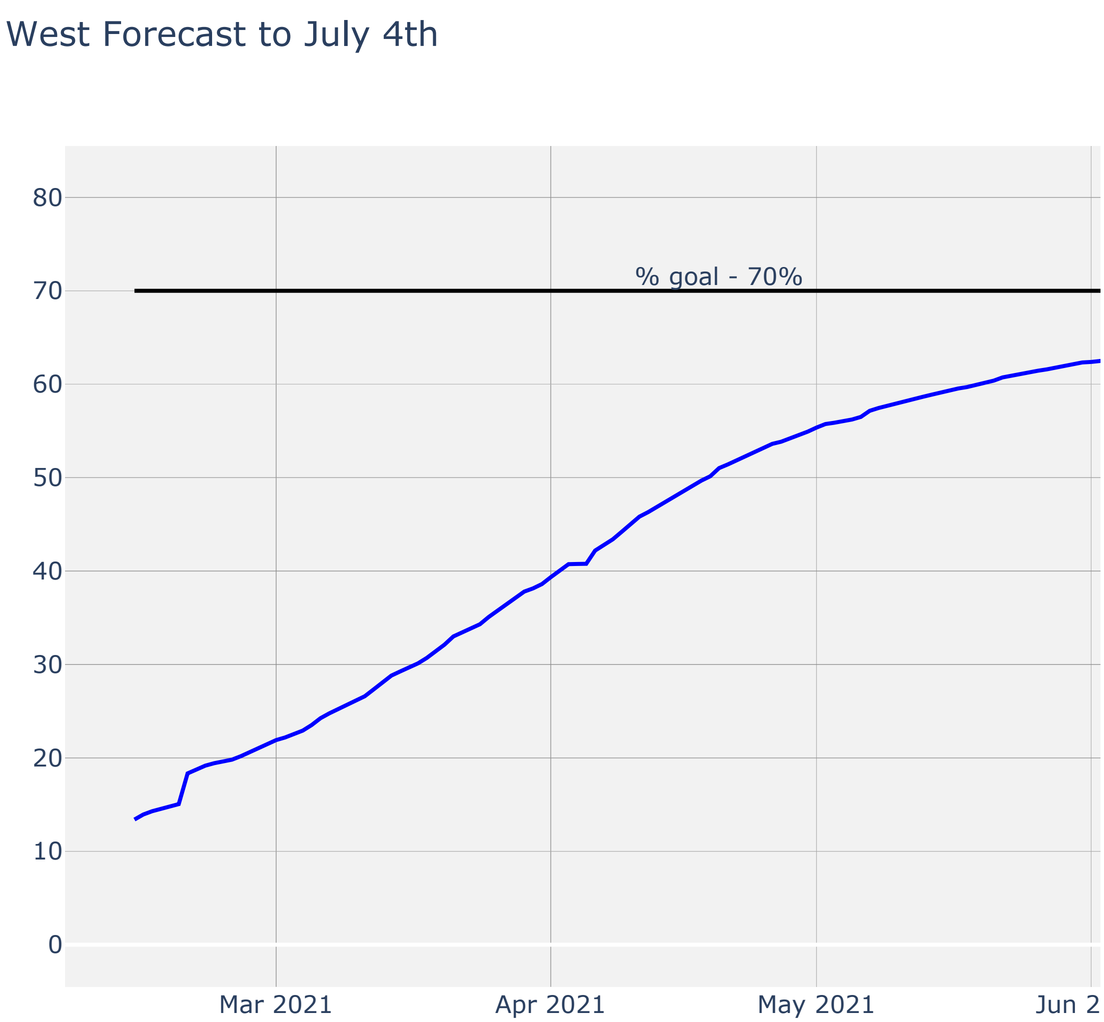
Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).

In [66]:
```
west_model_full.plot_diagnostics()
plt.tight_layout()
```



In [67]:
```
# forecast 21 days into the future using newly trained model
func.plot_forecast(west_model_full, ts1_west, steps=21, title='West Fo
                   file_name='west_forecast')
```

```
Forecast for 7/4/21: 65.85890405105232
```



The west region is projected to reach 65.86% of the adult population receiving at least one vaccine dose as of July 4th.

Midwest

Preprocessing

In [68]:

```
# create df, drop unused feature, and resample
ts1_midwest = ts1_region[ts1_region.Region == 'Midwest']
ts1_midwest = ts1_midwest.drop(columns='Region')
ts1_midwest = ts1_midwest.resample('D').asfreq()
display(ts1_midwest)
ts1_midwest.index
```

	Administered_Dose1_Recip_18PlusPop_Pct
Date	
2021-02-13	13.550000
2021-02-14	14.075000
2021-02-15	14.400000
2021-02-16	14.550000
2021-02-17	14.775000
...	...
2021-06-09	60.691667
2021-06-10	60.800000
2021-06-11	60.816667
2021-06-12	60.950000
2021-06-13	61.058333

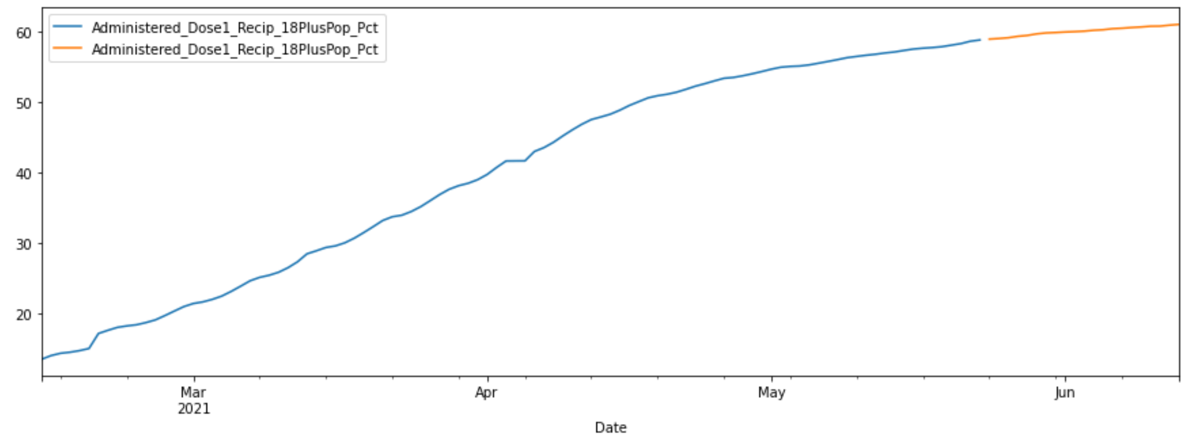
121 rows × 1 columns

Out[68]:

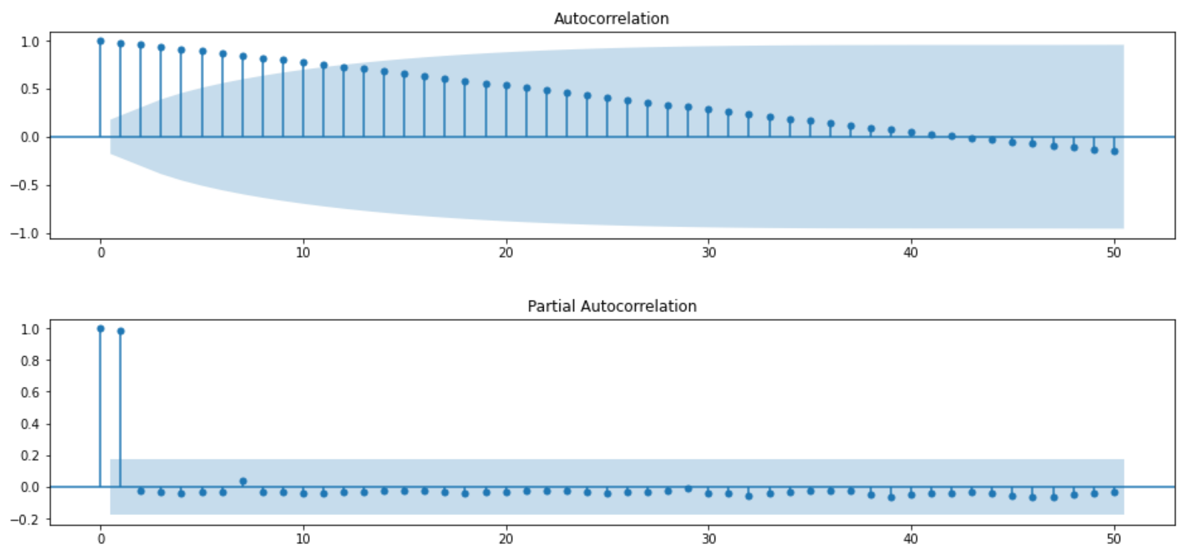
```
DatetimeIndex(['2021-02-13', '2021-02-14', '2021-02-15', '2021-02-16',
               '2021-02-17', '2021-02-18', '2021-02-19', '2021-02-20',
               '2021-02-21', '2021-02-22',
               ...
               '2021-06-04', '2021-06-05', '2021-06-06', '2021-06-07',
               '2021-06-08', '2021-06-09', '2021-06-10', '2021-06-11',
               '2021-06-12', '2021-06-13'],
              dtype='datetime64[ns]', name='Date', length=121, freq='D
```

In [69]:
```
#train test split
ts1_midwest_train = ts1_midwest.iloc[:-21]
ts1_midwest_test = ts1_midwest.iloc[-21:]

#ensure no overlap between train and test sets
fig, ax = plt.subplots()
ts1_midwest_train.plot(ax=ax, label='train')
ts1_midwest_test.plot(ax=ax, label='test')
```

Out[69]:
```
<AxesSubplot:xlabel='Date'>
```

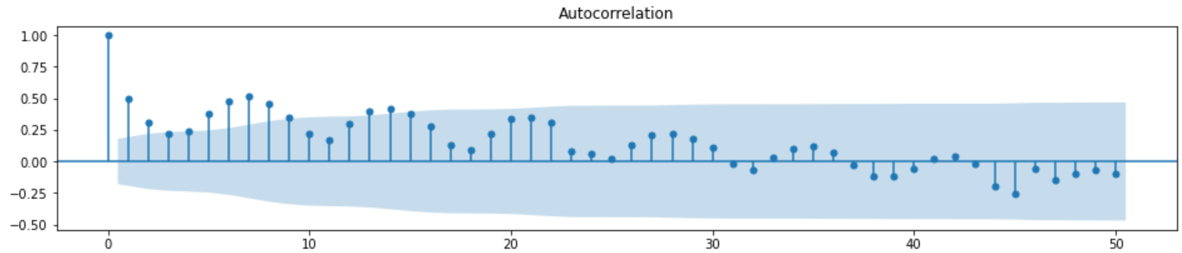


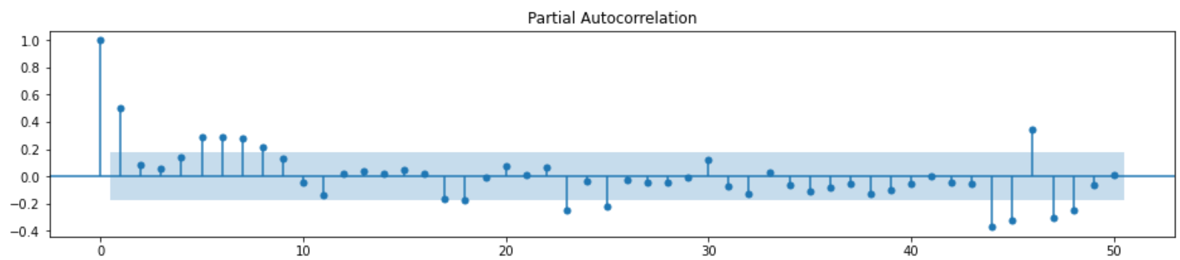
In [70]:
```
func.acf_pacf_plot(ts1_midwest)
```



In [71]:

```
func.acf_pacf_plot(ts1_midwest.diff().dropna())
```





The midwest shows more of a seasonal trend than national and west regions, so I'll assume the seasonal model will perform better than the ARIMA model.

Seasonal Model

In [72]:

```
# grid search optimal order parameters
func.grid_search_pdqs(ts1_midwest_train, max_range=3, s=7)
```

	order	seasonal order	AIC
370	(1, 1, 1)	(2, 0, 1, 7)	-32.148563
362	(1, 1, 1)	(1, 0, 2, 7)	-31.577813
397	(1, 1, 2)	(2, 0, 1, 7)	-30.705145
371	(1, 1, 1)	(2, 0, 2, 7)	-30.391593
605	(2, 1, 1)	(1, 0, 2, 7)	-29.710353
...	...	...	...
55	(0, 0, 2)	(0, 0, 1, 7)	734.781081
54	(0, 0, 2)	(0, 0, 0, 7)	756.418021
27	(0, 0, 1)	(0, 0, 0, 7)	887.330746
1	(0, 0, 0)	(0, 0, 1, 7)	961.584219
0	(0, 0, 0)	(0, 0, 0, 7)	1025.004307

729 rows × 3 columns

Out[72]:

	order	seasonal order	AIC
370	(1, 1, 1)	(2, 0, 1, 7)	-32.148563
362	(1, 1, 1)	(1, 0, 2, 7)	-31.577813
397	(1, 1, 2)	(2, 0, 1, 7)	-30.705145
371	(1, 1, 1)	(2, 0, 2, 7)	-30.391593
605	(2, 1, 1)	(1, 0, 2, 7)	-29.710353
...	...	...	...
55	(0, 0, 2)	(0, 0, 1, 7)	734.781081
54	(0, 0, 2)	(0, 0, 0, 7)	756.418021
27	(0, 0, 1)	(0, 0, 0, 7)	887.330746
1	(0, 0, 0)	(0, 0, 1, 7)	961.584219
0	(0, 0, 0)	(0, 0, 0, 7)	1025.004307

729 rows × 3 columns

In [73]:

```
# train full dataset using optimal order params found
midwest_model_s = tsa.SARIMAX(ts1_midwest,
                              order=(1,1,1),
                              seasonal_order=(2,0,1,7),
                              enforce_invertibility=False,
                              enforce_stationarity=False).fit()
midwest_model_s.summary()
```

Out[73]:

SARIMAX Results

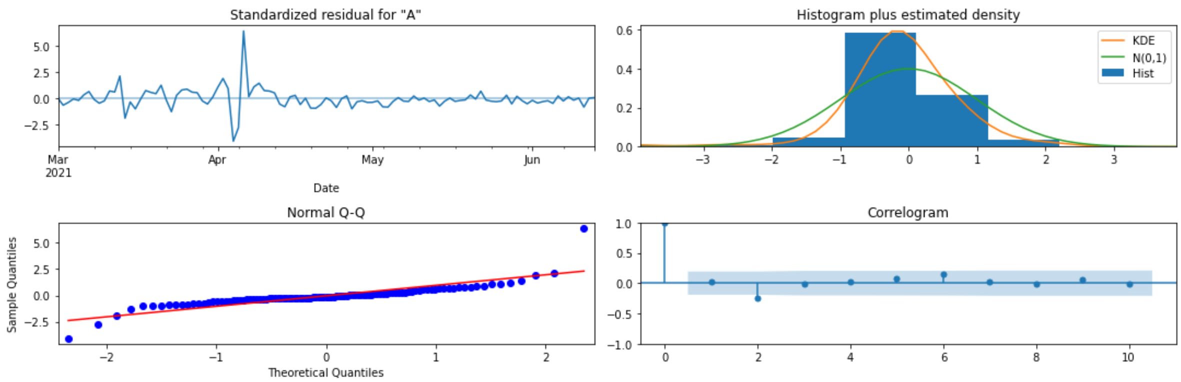
Dep. Variable:	Administered_Dose1_Recip_18PlusPop_Pct	**No. Observations:**	121
Model:	SARIMAX(1, 1, 1)x(2, 0, 1, 7)	**Log Likelihood**	39.839
Date:	Sat, 19 Jun 2021	**AIC**	-67.679
Time:	16:50:18	**BIC**	-51.755
Sample:	02-13-2021	**HQIC**	-61.226
	- 06-13-2021		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.9450	0.019	50.581	0.000	0.908	0.982
ma.L1	-0.8075	0.086	-9.405	0.000	-0.976	-0.639
ar.S.L7	0.8275	0.135	6.128	0.000	0.563	1.092
ar.S.L14	0.0295	0.109	0.270	0.787	-0.184	0.243
ma.S.L7	-1.0000	690.795	-0.001	0.999	-1354.934	1352.934
sigma2	0.0225	15.515	0.001	0.999	-30.387	30.432

Ljung-Box (L1) (Q):	0.10	**Jarque-Bera (JB):**	1350.61
Prob(Q):	0.75	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.10	**Skew:**	1.87
Prob(H) (two-sided):	0.00	**Kurtosis:**	20.17

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

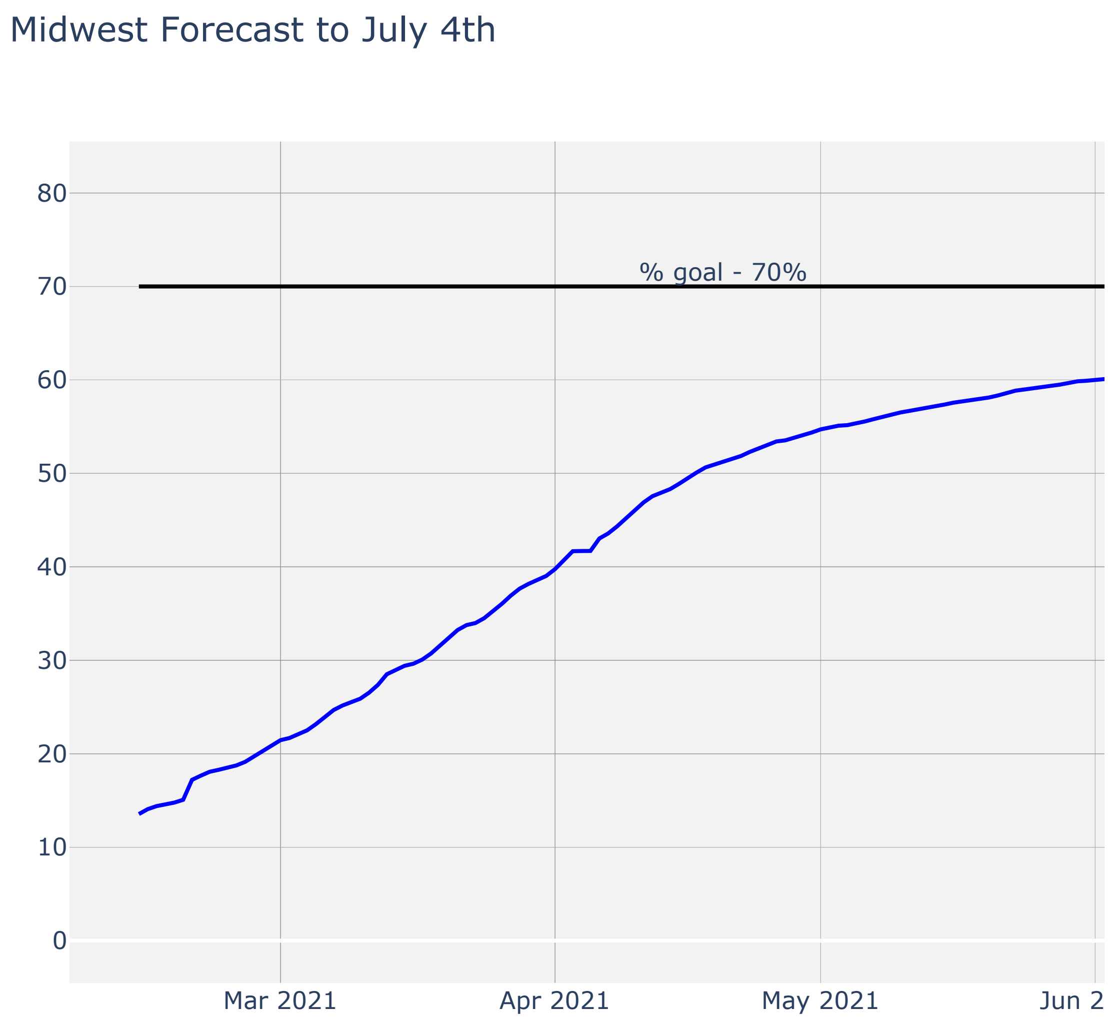
In [74]:
```
midwest_model_s.plot_diagnostics()
plt.tight_layout()
```



Forecast

In [75]:
```
func.plot_forecast(midwest_model_s, ts1_midwest, steps=21, title='Midwe
                   file_name='midwest_forecast')
```

```
Forecast for 7/4/21: 63.152182404186235
```



The midwest region is projected to reach 63.15% of the adult population receiving at least one vaccine dose as of July 4th.

South

Preprocessing

In [76]:
```
# create df, drop unused feature, and resample
ts1_south = ts1_region[ts1_region.Region == 'South']
ts1_south = ts1_south.drop(columns='Region')
ts1_south = ts1_south.resample('D').asfreq()
display(ts1_south)
ts1_south.index
```

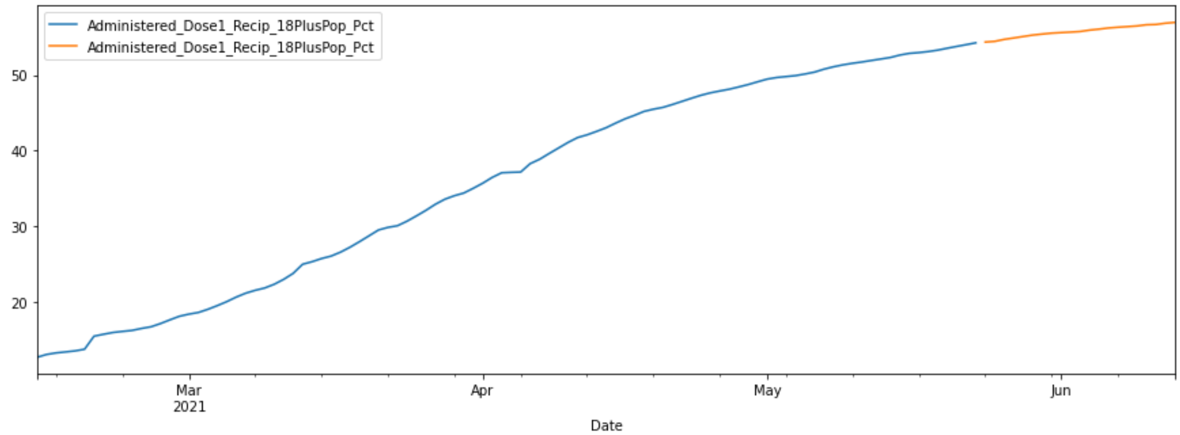
	Administered_Dose1_Recip_18PlusPop_Pct
Date	
2021-02-13	12.747059
2021-02-14	13.117647
2021-02-15	13.323529
2021-02-16	13.452941
2021-02-17	13.588235
...	...
2021-06-09	56.477778
2021-06-10	56.633333
2021-06-11	56.672222
2021-06-12	56.838889
2021-06-13	56.944444

121 rows × 1 columns

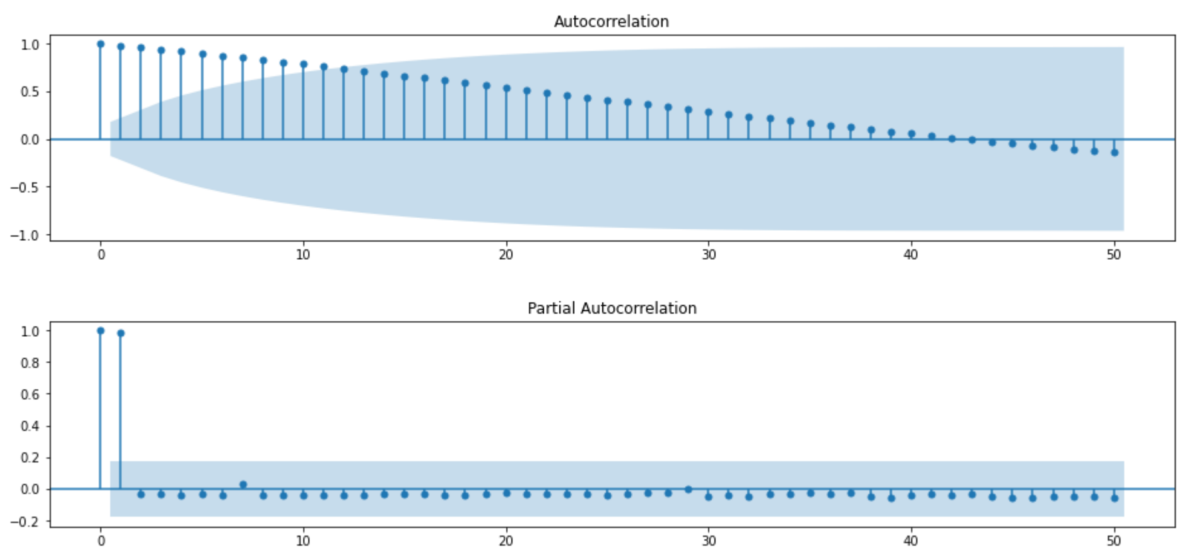
Out[76]:
```
DatetimeIndex(['2021-02-13', '2021-02-14', '2021-02-15', '2021-02-16',
               '2021-02-17', '2021-02-18', '2021-02-19', '2021-02-20',
               '2021-02-21', '2021-02-22',
               ...
               '2021-06-04', '2021-06-05', '2021-06-06', '2021-06-07',
               '2021-06-08', '2021-06-09', '2021-06-10', '2021-06-11',
               '2021-06-12', '2021-06-13'],
              dtype='datetime64[ns]', name='Date', length=121, freq='D
```

In [77]:
```
#train test split
ts1_south_train = ts1_south.iloc[:-21]
ts1_south_test = ts1_south.iloc[-21:]

#ensure no overlap between train and test sets
fig, ax = plt.subplots()
ts1_south_train.plot(ax=ax, label='train')
ts1_south_test.plot(ax=ax, label='test')
```

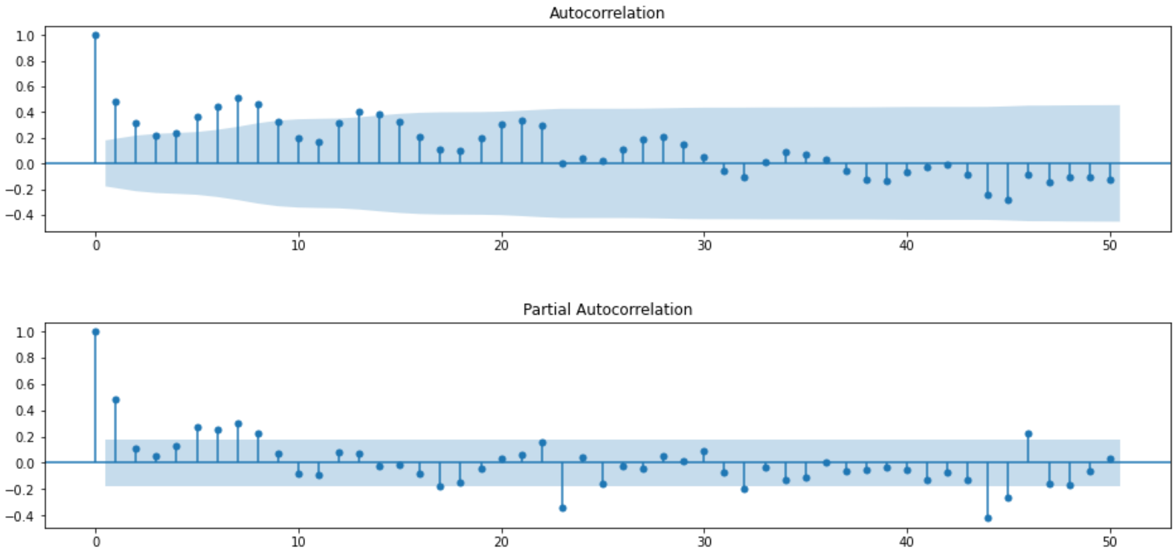
Out[77]: <AxesSubplot:xlabel='Date'>



In [78]:
```
func.acf_pacf_plot(ts1_south)
```



In [79]:
```
func.acf_pacf_plot(ts1_south.diff().dropna())
```



Similar to the midwest, the south also shows significant seasonality. We'll again assume that the seasonal model will perform best.

Seasonal Model

In [80]:

```
func.grid_search_pdqs(ts1_south_train, max_range=3, s=7)
```

	order	seasonal order	AIC
362	(1, 1, 1)	(1, 0, 2, 7)	-61.385410
370	(1, 1, 1)	(2, 0, 1, 7)	-61.314246
397	(1, 1, 2)	(2, 0, 1, 7)	-60.725034
605	(2, 1, 1)	(1, 0, 2, 7)	-60.068558
371	(1, 1, 1)	(2, 0, 2, 7)	-59.677571
...	...	...	...
2	(0, 0, 0)	(0, 0, 2, 7)	785.260831
1	(0, 0, 0)	(0, 0, 1, 7)	839.015638
27	(0, 0, 1)	(0, 0, 0, 7)	866.854325
28	(0, 0, 1)	(0, 0, 1, 7)	941.850251
0	(0, 0, 0)	(0, 0, 0, 7)	1004.271944

729 rows × 3 columns

Out[80]:

	order	seasonal order	AIC
362	(1, 1, 1)	(1, 0, 2, 7)	-61.385410
370	(1, 1, 1)	(2, 0, 1, 7)	-61.314246
397	(1, 1, 2)	(2, 0, 1, 7)	-60.725034
605	(2, 1, 1)	(1, 0, 2, 7)	-60.068558
371	(1, 1, 1)	(2, 0, 2, 7)	-59.677571
...	...	...	...
2	(0, 0, 0)	(0, 0, 2, 7)	785.260831
1	(0, 0, 0)	(0, 0, 1, 7)	839.015638
27	(0, 0, 1)	(0, 0, 0, 7)	866.854325
28	(0, 0, 1)	(0, 0, 1, 7)	941.850251
0	(0, 0, 0)	(0, 0, 0, 7)	1004.271944

729 rows × 3 columns

In [81]:
```
south_model = tsa.SARIMAX(ts1_south,
                          order=(1,1,1),
                          seasonal_order=(1,0,2,7),
                          enforce_stationarity=False,
                          enforce_invertibility=False).fit()
south_model.summary()
```

Out[81]:

SARIMAX Results

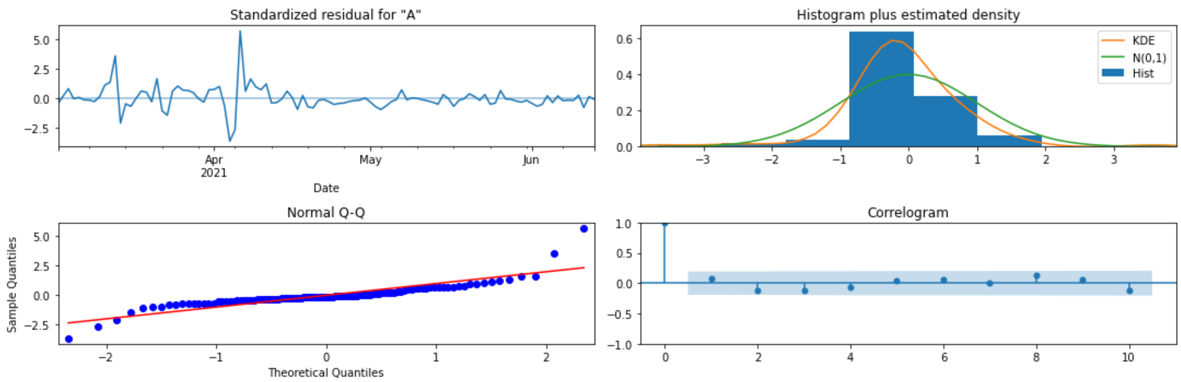
Dep. Variable:	Administered_Dose1_Recip_18PlusPop_Pct	**No. Observations:**	121
Model:	SARIMAX(1, 1, 1)x(1, 0, [1, 2], 7)	**Log Likelihood**	57.515
Date:	Sat, 19 Jun 2021	**AIC**	-103.030
Time:	16:54:04	**BIC**	-87.164
Sample:	02-13-2021	**HQIC**	-96.602
	- 06-13-2021		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	0.9423	0.021	44.170	0.000	0.900	0.984
ma.L1	-0.8585	0.055	-15.598	0.000	-0.966	-0.751
ar.S.L7	0.8687	0.050	17.241	0.000	0.770	0.967
ma.S.L7	-0.8836	797.707	-0.001	0.999	-1564.360	1562.593
ma.S.L14	-0.1164	92.781	-0.001	0.999	-181.963	181.730
sigma2	0.0161	12.879	0.001	0.999	-25.226	25.259

Ljung-Box (L1) (Q):	0.70	**Jarque-Bera (JB):**	632.12
Prob(Q):	0.40	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.08	**Skew:**	1.61
Prob(H) (two-sided):	0.00	**Kurtosis:**	14.64

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

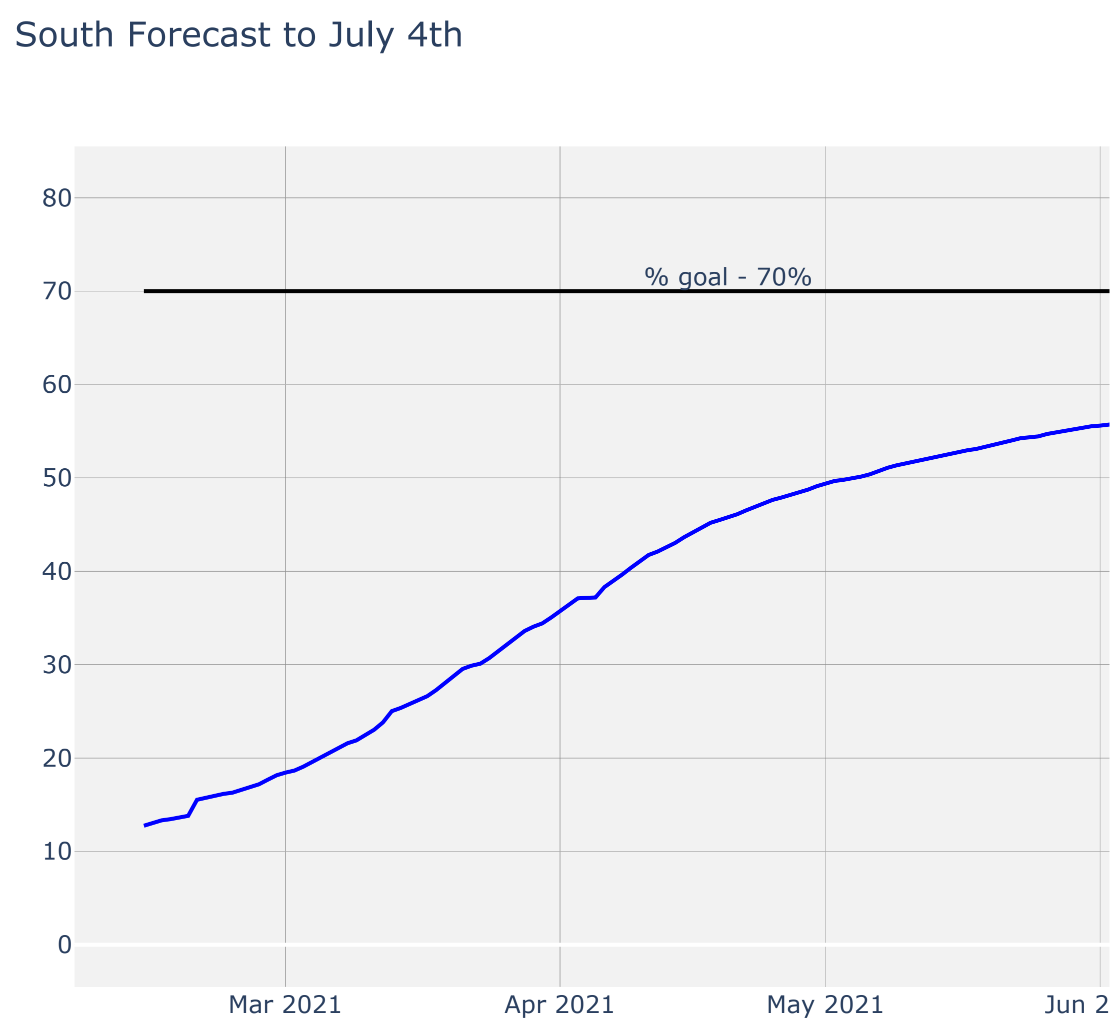
In [82]:
```
south_model.plot_diagnostics();
plt.tight_layout()
```



Forecast

In [83]:
```
func.plot_forecast(south_model, ts1_south, steps=21, title='South Forec
                                 file_name='south_forecast')
```

```
Forecast for 7/4/21: 59.244956235004196
```



The south projects only reaching 59.24% of the adult population by July 4th, representing **the largest opportunity area for vaccine campaign activities.**

Administration Rate

Based on discussion on the US national news, one would believe the country has a surplus of vaccines. I wanted to dig into this at a regional level to understand if reallocating vaccines to areas where people are more interested might help the country's overall percentages.

To do so, I engineered a feature *Administration Rate* to represent how many vaccines were administered per 1 vaccine distributed.

- A value of 1.0 would indicate a jurisdiction is administering every single vaccine they have. This might indicate the region could administer more if they had more available.
- A value just under 1.0 is optimal, meaning vaccines are being appropriately distributed and not wasted.
- Lower values indicate opportunity to either reallocate unused vaccines or encourage the population to use what is available to them. For example, a value of 0.5 indicates the region is only administering half of the vaccines they have.

In [84]:

```
# parse out relevant features
allocation_df = full_dataset[['Date', 'Location', 'Distributed', 'Admir
```

In [85]:

```
# engineer availability ratio feature, reset index, and
# begin analysis at the same date as the rest of the analysis
allocation_df['Administration Rate'] = allocation_df['Administered'] /
allocation_df['Date'] = pd.to_datetime(allocation_df['Date'])
allocation_df.set_index('Date', inplace=True)
allocation_df=allocation_df[:'2021-02-13']
```

```
<ipython-input-85-a48a68e75390>:3: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-

<ipython-input-85-a48a68e75390>:4: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
```

In [86]:

```
# calculate region using previously defined function, drop irrelevant c
allocation_df['Region'] = allocation_df['Location'].map(lambda x: regic
allocation_df.drop(columns=['Location', 'Distributed', 'Administered'],
allocation_df
```

Out[86]:

	Administration Rate	Region
Date		
2021-06-13	0.892601	Midwest
2021-06-13	0.781465	South
2021-06-13	0.726312	South
2021-06-13	0.879236	West
2021-06-13	0.959523	West
...	...	...
2021-02-14	0.773679	Northeast
2021-02-14	0.617341	Northeast
2021-02-14	0.880225	Midwest
2021-02-14	0.811275	West
2021-02-14	0.835553	South

7800 rows × 2 columns

In [87]:

```
#drop null values
allocation_df = allocation_df[allocation_df['Region'] != '']
```

Because there is seasonality in the data - day of the week matters - a weekly average will more clearly show overall trends without as much noise. The following cells parse each region into their own dataframe to be resampled, then brings them back together for graphing.

In [88]:

```
#parse south region and resample
south_allocation = allocation_df[allocation_df['Region'] == 'South']
south_allocation = south_allocation.drop(columns='Region').resample('W
south_allocation['Region'] = 'South'
```

In [89]:

```
#parse west region and resample
west_allocation = allocation_df[allocation_df['Region'] == 'West']
west_allocation = west_allocation.drop(columns='Region').resample('W').
west_allocation['Region'] = 'West'
```

In [90]:
```
#parse midwest and resample
midwest_allocation = allocation_df[allocation_df['Region'] == 'Midwest
midwest_allocation = midwest_allocation.drop(columns='Region').resample
midwest_allocation['Region'] = 'Midwest'
```

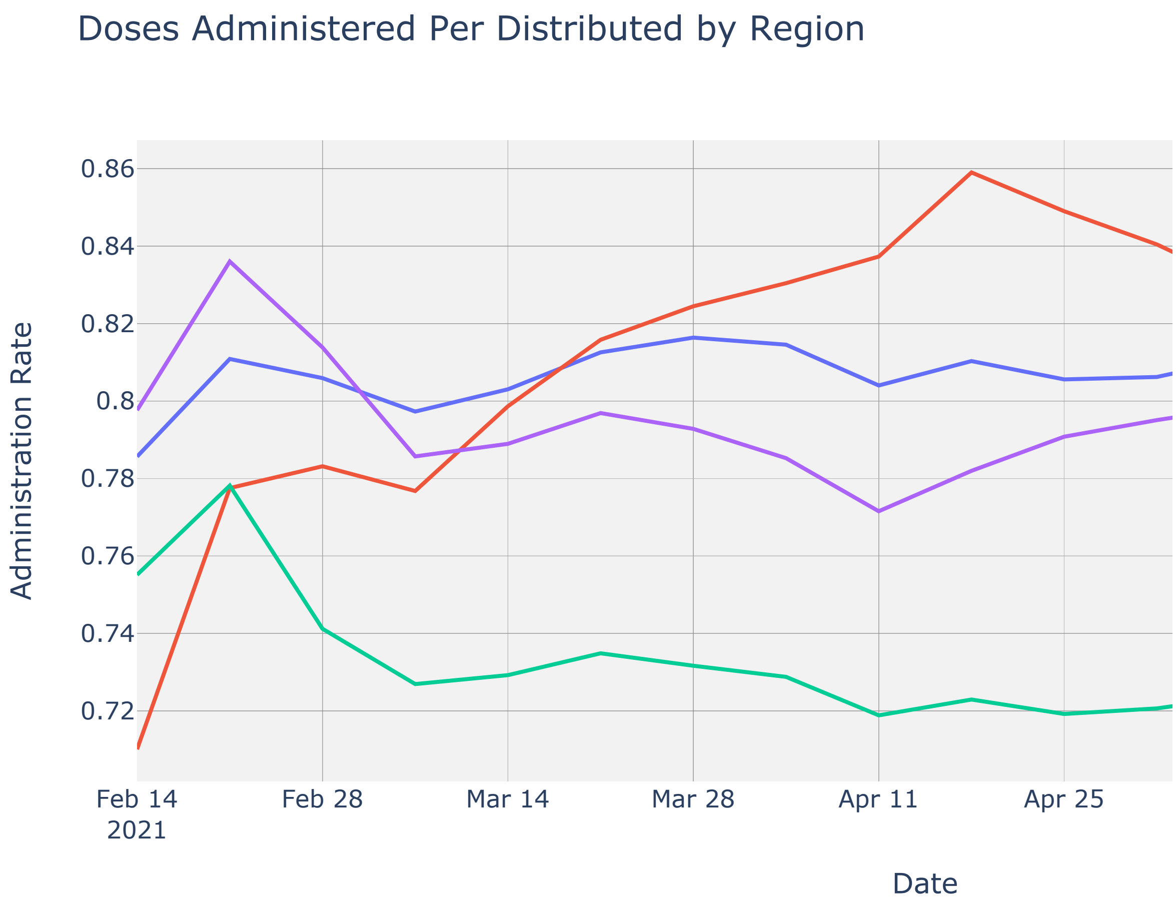
In [91]:
```
#parse northeast and resample
northeast_allocation = allocation_df[allocation_df['Region'] == 'Northe
northeast_allocation = northeast_allocation.drop(columns='Region').resa
northeast_allocation['Region'] = 'Northeast'
```

In [92]:
```
#combine back into one df for easy graphing
allocation_df = pd.concat([midwest_allocation,
                           northeast_allocation,
                           south_allocation,
                           west_allocation], axis=0)
```

In [93]:
```
#check for data leakage
allocation_df['Region'].value_counts()
```

Out[93]:
```
South        18
Midwest      18
Northeast    18
West         18
Name: Region, dtype: int64
```

In [94]:
```
#visualize availability ratios by region
fig = px.line(x=allocation_df.index,
              y=allocation_df['Administration Rate'],
              color=allocation_df['Region'],
             title='Doses Administered Per Distributed by Region',
             labels={'x': 'Date',
                     'y': 'Administration Rate',
                     'color': 'Legend'})
#styling
fig.update_layout(plot_bgcolor='#f2f2f2', height=500, width=1000)

#save fig
fig.write_image('./images/Administration Rate Over Time by Region.jpg')
fig.show()
```



The availability ratio shows the south lagging significantly in the number of doses administered per vaccine distributed. This leads us to believe that the challenge is not a lack of vaccine availability, rather there may be a lack of interest from the population in getting vaccinated.

Summary & Recommendations

KEY TAKEAWAYS

Based on an analysis of the CDC's COVID-19 Vaccine Administration tracker as of June 13, 2021, it is predicted that the US will not reach their goal of administering at least one vaccine dose to 70% of the adult population. However, the goal is not far off, and additional campaigning in the areas lagging behind may help close the gap.

The northeast region is leading the nation in vaccine administration, having achieved the 70% administration goal in mid-May and continuing an upward trajectory since then. The south is lagging behind in both vaccine administration as a percentage of the adult population and in efficiently administering the vaccines distributed to the region.

RECOMMENDATIONS

In the remaining weeks leading up to July 4th, the Biden administration should take the following actions to increase the chances of meeting their goal:

- Continue community-based vaccine education and local outreach efforts, focusing on this aspect of the campaign most
- Launch a nation-wide educational campaign explaining the benefits and risks of COVID-19 vaccination and debunking common misconceptions about the vaccines
- Focus investments in the south

Future Enhancements

- Codify references to the optimal order and seasonal order found in grid search for use when training the actual model
- Calculate mean squared error within model validation step

Appendix

Simplified plot of regional trends

In [95]:
```
#plot timeseries in range
fig = px.line(ts1_region, color='Region',
              title="Vaccine Administration by Region (% of adult pop.
              range_x=('2021-02-12', '2021-07-04'),
              labels={'value': '% of Adult Pop. with ≥1 Dose'})

#plot horizontal line at goal of 70% first dose administered
fig.add_trace(go.Scatter(
    x=[0, '2021-04-20', '2021-07-04'],
    y=[70, 70, 70],
    mode="lines+text",
    line=go.scatter.Line(color='black'),
    name="% goal - 70%",
    text=[None, "National Goal: 70%", None],
    textposition="top center",
    textfont={'size':12}))

#styling
fig.update_layout(plot_bgcolor='#f2f2f2', height=500, width=1000)

#save fig
fig.write_image(f'./images/simplified_regional_trend.jpg')
fig.show()
```