In [16]:
```
#General Libraries for

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
from matplotlib.pyplot import figure
from sklearn.metrics import mean_absolute_error
import statsmodels.tsa.statespace.sarimax
from statsmodels.tsa.stattools import adfuller
import itertools

import warnings
warnings.filterwarnings('ignore')
warnings.warn('DelftStack')
warnings.warn('Do not show this message')
print("No Warning Shown")
```

```
No Warning Shown
```

In [2]:
```
df = pd.read_csv('zillow_data.csv')
```

Step 2: Data Preprocessing

In [4]:
```
def get_datetimes(df):

    """
    Takes a dataframe:
    returns only those column names that can be converted into datetime
    as datetime objects.
    NOTE number of returned columns may not match total number of colum
    """

    return pd.to_datetime(df.columns.values[7:], format='%Y-%m')
```

In [5]:
```
get_datetimes(df)
```

Out[5]:
```
DatetimeIndex(['1996-04-01', '1996-05-01', '1996-06-01', '1996-07-01',
               '1996-08-01', '1996-09-01', '1996-10-01', '1996-11-01',
               '1996-12-01', '1997-01-01',
               ...
               '2017-07-01', '2017-08-01', '2017-09-01', '2017-10-01',
               '2017-11-01', '2017-12-01', '2018-01-01', '2018-02-01',
               '2018-03-01', '2018-04-01'],
              dtype='datetime64[ns]', length=265, freq=None)
```

Step 3: EDA and Visualization

In [6]:
```
font = {'family' : 'normal',
        'weight' : 'bold',
        'size'   : 11}

matplotlib.rc('font', **font)

# NOTE: if you visualizations are too cluttered to read, try calling 'p
```

Step 4: Reshape from Wide to Long Format

In [7]:
```
def melt_total_data(df):
    """
    Takes the zillow_data dataset in wide form or a subset of the zillo
    Returns a long-form datetime dataframe
    with the datetime column names as the index and the values as the '

    If more than one row is passes in the wide-form dataset, the values
    will be the mean of the values from the datetime columns in all of
    """

    melted = pd.melt(df, id_vars=['RegionName', 'RegionID', 'SizeRank',
    melted['time'] = pd.to_datetime(melted['time'], infer_datetime_form
    melted = melted.dropna(subset=['value'])
    return melted .groupby('time').aggregate({'value':'mean'})
```

In [8]:
```
def melt_data(df):
    """
    Takes the zillow_data dataset in wide form or a subset of the zillo
    Returns a long-form datetime dataframe
    with the datetime column names as the index and the values as the '

    If more than one row is passes in the wide-form dataset, the values
    will be the mean of the values from the datetime columns in all of
    """

    melted = pd.melt(df, id_vars=['RegionName', 'RegionID', 'SizeRank',
    melted['time'] = pd.to_datetime(melted['time'], infer_datetime_form
    melted = melted.dropna(subset=['value'])
    return melted
```

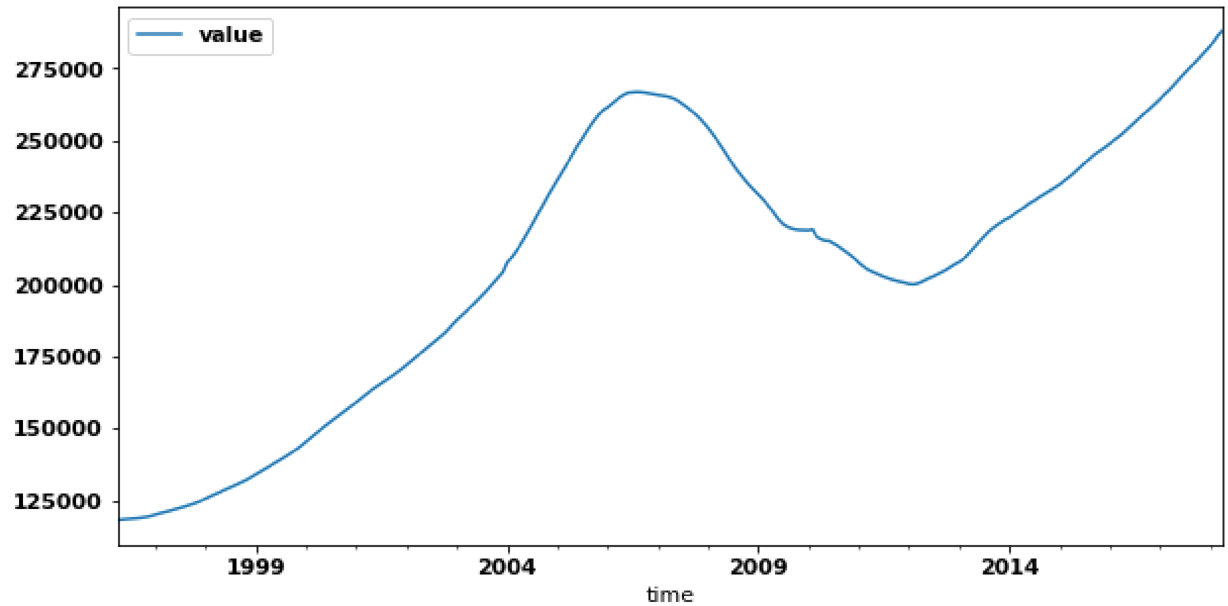
Step 5: ARIMA Modeling

In [9]:
```
#Create Initial Dataframe for Model

total_df = melt_total_data(df)
```

In [10]:
```python
#Plot Model to Determine potential patterns

total_df.plot(figsize=(10,5))
```

Out[10]:
```
<AxesSubplot:xlabel='time'>
```

```
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
```



In [11]:
```python
#Conducting Dickey Fuller Test to Determine Stationarity

def adtest(frame):
    dickeyfuller = adfuller(frame)
    ad_results = pd.DataFrame(dickeyfuller[0:4], index=['Test Statistic
                                                        'p-value',
                                                        '# Lags Used',
                                                        'Number of Observations Used

    return ad_results.loc['p-value']

adtest(total_df)
```

Out[11]:
```
0    0.339082
Name: p-value, dtype: float64
```

In [12]:

```
#Due to Dickey Fuller test returning a P Value greater than 0.05, diffe

good_diff_values = []

for n in range(1, 60, 1):
    total_df_diff = total_df.diff(n).dropna()
    p_val = adtest(total_df_diff)
    if p_val[0] < 0.051:
        good_diff_values.append([n, p_val[0]])

differencing_vals = pd.DataFrame(good_diff_values).sort_values(by=0, as

differencing_vals.head()
```

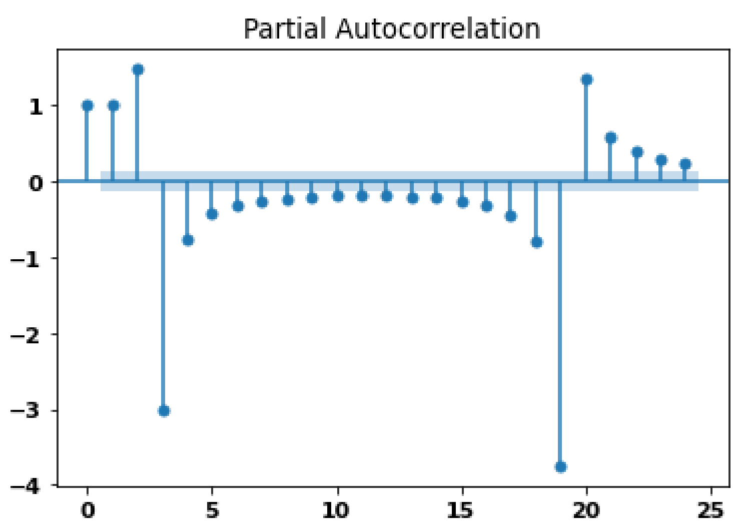
Out[12]:

	0	1
0	19	0.017197
1	20	0.009884
2	21	0.021668
3	22	0.015678
4	23	0.022229

In [13]:

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf

for item in differencing_vals[0]:
    plot_pacf(total_df.diff(item).dropna());
    # plot_pacf(total_df.diff(19).dropna());
```

```
findfont: Font family ['normal'] not found. Falling back to DejaVu Sans.
```



In [14]:
```
#Splitting Train and Test Data

X_train = total_df.head(265-12)
y_train = total_df.tail(12)
```

In [17]:
```
#Iterate through potential pdq values for total dataset

# Define the p, d and q parameters to take any value between 0 and 2
p = d = q = range(0,4,1)

# Generate all different combinations of p, q and q triplets
pdq = list(itertools.product(p, d, q))

# Generate all different combinations of seasonal p, q and q triplets (

pdqs = [(x[0], x[1], x[2], 12) for x in list(itertools.product(p, d, q)
```

In [18]:
```
# #Ascertain Best Combos

# from sklearn.metrics import mean_absolute_error

# import statsmodels

# best_iteration = []

# for combo in pdq:
#     for seasonal_combo in pdqs:
#         final_model = statsmodels.tsa.statespace.sarimax.SARIMAX(X_tr
#                                                                 orde
#                                                                 seas
#                                                                 enfc
#                                                                 enfc

#         final_model_fit = final_model.fit()

#         preds = final_model_fit.get_forecast(steps = 12)

#         preds = preds.summary_frame()[['mean']]

#         mae = mean_absolute_error(preds, y_train)

#         comp_error = mae / int(y_train.tail(1)['value'])

#         best_iteration.append([combo, seasonal_combo, mae, comp_error

#         print([combo, seasonal_combo, mae, comp_error])
```

In [19]:
```
# #Ascertain Best Combination:

# best_iteration = pd.DataFrame(best_iteration)

# best_iteration.columns = ['pdq', 'PDQS', 'MAE', 'MAE / M12']

# best_iteration = best_iteration.sort_values(by='MAE', ascending = Fal

# best_iteration['MAE'] = round(best_iteration['MAE'])

# #Isolate best features

# best_pdq = list(best_iteration[['pdq']].tail(1)['pdq'])[0]
# best_PDQS = list(best_iteration[['PDQS']].tail(1)['PDQS'])[0]

# #Saving best features below:

# best_iteration.tail(1)

# #     pdq PDQS    MAE MAE / M12
# # 2119    (2, 0, 1)   (0, 1, 3, 12)   88.0    0.000307

best_pdq = (2,0,1)
best_PDQS = (0,1,3,12)
```

In [20]:
```
#Fit Best Model

import statsmodels

final_model = statsmodels.tsa.statespace.sarimax.SARIMAX(X_train,
                                                  order = best_pdq,
                                                  seasonal_order = best_PDQS,
                                                  enforce_stationarity = False,
                                                  enforce_invertibility = False)

fit_model = final_model.fit()
```

In [21]:
```
1 fit_model.summary()
```

Out[21]:

SARIMAX Results

Dep. Variable:	value	**No. Observations:**	253
Model:	SARIMAX(2, 0, 1)x(0, 1, [1, 2, 3], 12)	**Log Likelihood**	-1519.133
Date:	Mon, 25 Oct 2021	**AIC**	3052.266
Time:	15:43:01	**BIC**	3075.458
Sample:	04-01-1996	**HQIC**	3061.648
	- 04-01-2017		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	1.9791	0.043	46.081	0.000	1.895	2.063
ar.L2	-0.9789	0.043	-22.730	0.000	-1.063	-0.895
ma.L1	-0.4010	0.108	-3.724	0.000	-0.612	-0.190
ma.S.L12	0.4827	0.124	3.897	0.000	0.240	0.725
ma.S.L24	-1.0618	0.105	-10.159	0.000	-1.267	-0.857
ma.S.L36	0.3717	0.090	4.135	0.000	0.196	0.548
sigma2	1.382e+05	2.15e+04	6.416	0.000	9.6e+04	1.8e+05

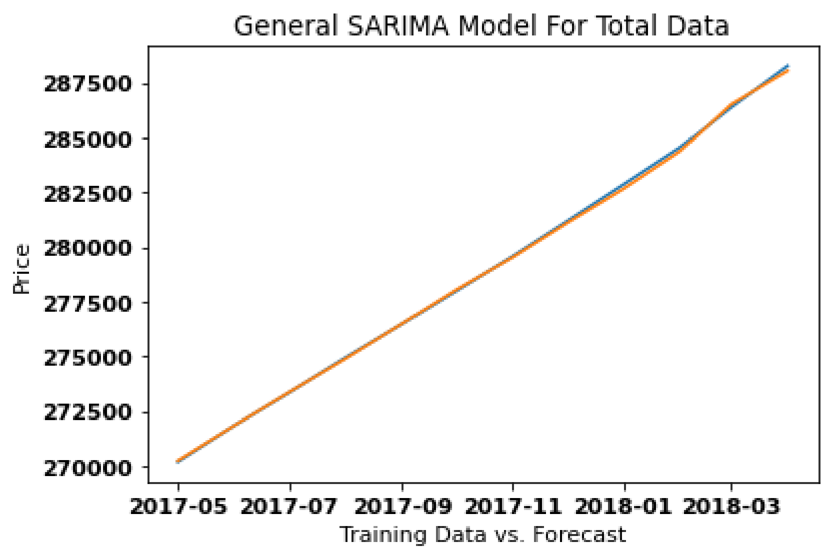
Ljung-Box (L1) (Q):	0.70	**Jarque-Bera (JB):**	1287.79
Prob(Q):	0.40	**Prob(JB):**	0.00
Heteroskedasticity (H):	0.49	**Skew:**	0.13
Prob(H) (two-sided):	0.00	**Kurtosis:**	15.34

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 6.7e+14. Standard errors may be unstable.

In [74]:

```
#Get Preds and Map Against y_train

preds = fit_model.get_forecast(steps=12).summary_frame()['mean']

plt.plot(preds)
plt.plot(y_train)

print(f'Mean Absolute Error: {mean_absolute_error(preds, y_train)}')

plt.title('General SARIMA Model For Total Data')
plt.xlabel('Training Data vs. Forecast')
plt.ylabel('Price');

```

```
Mean Absolute Error: 88.33125573327318
```



In [24]:

```
#Creating dataframe to assess future values of all regions

final_df = melt_data(df)

final_df['time'] = pd.to_datetime(final_df['time'])

final_df.set_index('time', inplace=True)

final_df
```

Out[24]:

time	RegionName	RegionID	SizeRank	City	State	Metro	CountyName	value
1996-04-01	60657	84654	1	Chicago	IL	Chicago	Cook	334200.0
1996-04-01	75070	90668	2	McKinney	TX	Dallas-Fort Worth	Collin	235700.0
1996-04-01	77494	91982	3	Katy	TX	Houston	Harris	210400.0
1996-04-01	60614	84616	4	Chicago	IL	Chicago	Cook	498100.0
1996-04-01	79936	93144	5	El Paso	TX	El Paso	El Paso	77300.0
...	...	...	...	...	...	...	...	...
2018-04-01	1338	58333	14719	Ashfield	MA	Greenfield Town	Franklin	209300.0
2018-04-01	3293	59107	14720	Woodstock	NH	Claremont	Grafton	225800.0
2018-04-01	40404	75672	14721	Berea	KY	Richmond	Madison	133400.0
2018-04-01	81225	93733	14722	Mount Crested Butte	CO	NaN	Gunnison	664400.0
2018-04-01	89155	95851	14723	Mesquite	NV	Las Vegas	Clark	357200.0

3744704 rows × 8 columns

In [25]:

```
#Isolating all regions

regions = pd.DataFrame(final_df['RegionID'].value_counts())

#Isolating Regions with complete data sets

complete_regions = regions[regions['RegionID'] == 265]

#Isolating regions that have experienced the most growth in the last ye

complete_regions = complete_regions.reset_index()

complete_regions.columns = ['RegionID', 'DataPoints']

annual_growth = complete_regions[['RegionID']]
```

In [26]:

```
#Create Columns to Compare Annual growth

annual_growth['Current Year'] = pd.to_datetime('2018-04-01')
annual_growth['Previous Year'] = pd.to_datetime('2017-04-01')
```

In [27]:

```
merge_table = final_df.reset_index()

merge_table['time'] = pd.to_datetime(merge_table['time'])

merge_table
```

Out[27]:

	time	RegionName	RegionID	SizeRank	City	State	Metro	CountyName	v
0	1996-04-01	60657	84654	1	Chicago	IL	Chicago	Cook	3342
1	1996-04-01	75070	90668	2	McKinney	TX	Dallas-Fort Worth	Collin	2357
2	1996-04-01	77494	91982	3	Katy	TX	Houston	Harris	2104
3	1996-04-01	60614	84616	4	Chicago	IL	Chicago	Cook	4981
4	1996-04-01	79936	93144	5	El Paso	TX	El Paso	El Paso	773
...	...	...	...	...	...	...	...	...	
3744699	2018-04-01	1338	58333	14719	Ashfield	MA	Greenfield Town	Franklin	2093
3744700	2018-04-01	3293	59107	14720	Woodstock	NH	Claremont	Grafton	2258
3744701	2018-04-01	40404	75672	14721	Berea	KY	Richmond	Madison	1334
3744702	2018-04-01	81225	93733	14722	Mount Crested Butte	CO	NaN	Gunnison	6644
3744703	2018-04-01	89155	95851	14723	Mesquite	NV	Las Vegas	Clark	3572

3744704 rows × 9 columns

In [28]:
```
# #Joining DataFrames to get current and previous values

growth_table =  annual_growth.merge(merge_table,
                           how='inner', left_on=['Current Year', 'Regio

growth_table = growth_table[['Current Year', 'Previous Year', 'RegionID

growth_table.columns = ['Current Year', 'Previous Year', 'RegionID', 't

growth_table = growth_table.merge(merge_table, how='inner',
                                 left_on=['Previous Year', 'RegionID']

growth_table = growth_table[['RegionID', 'Previous Year', 'Current Year

growth_table.columns = ['RegionID', 'Previous Year', 'Current Year', 'P

growth_table['Growth'] = growth_table['Current Value'] / growth_table['

#Isolating Top 20 Regions that Grew between 2017 and 2018

top_regions = growth_table.sort_values(by='Growth', ascending = False).

top_regions
```

Out[28]:

	RegionID	Previous Year	Current Year	Previous Value	Current Value	Growth
10656	60610	2017-04-01	2018-04-01	123800.0	186700.0	0.508078
6050	66014	2017-04-01	2018-04-01	36800.0	52900.0	0.437500
12044	60607	2017-04-01	2018-04-01	131200.0	188300.0	0.435213
12183	60561	2017-04-01	2018-04-01	141500.0	202000.0	0.427562
8174	73219	2017-04-01	2018-04-01	67200.0	95500.0	0.421131
...	...	...	...	...	...	...
2214	72702	2017-04-01	2018-04-01	87000.0	110800.0	0.273563
6359	98652	2017-04-01	2018-04-01	58500.0	74500.0	0.273504
6740	63882	2017-04-01	2018-04-01	90400.0	115000.0	0.272124
12891	73115	2017-04-01	2018-04-01	86400.0	109900.0	0.271991
10698	97528	2017-04-01	2018-04-01	1772600.0	2254100.0	0.271635

100 rows × 6 columns

In [29]:
```
#Creating function to get forecast by region

region_melt = melt_data(df)

def get_2019_forecast(Region_ID):

    X_train_region = region_melt[region_melt['RegionID'] == Region_ID]

    X_train_region['time'] = pd.to_datetime(X_train_region['time'])

    X_train_region.set_index('time', inplace = True)

    X_train_region = X_train_region[['value']]

    regional_model = statsmodels.tsa.statespace.sarimax.SARIMAX(X_train
                                                 order = best_pdq,
                                                 seasonal_order = best_PDQS,
                                                 enforce_stationarity = False
                                                 enforce_invertibility = Fals

    regional_model_fit = regional_model.fit()

    regional_preds = regional_model_fit.get_forecast(12)

    regional_preds_df = regional_preds.summary_frame()[['mean']]

    return [Region_ID, int(regional_preds_df[regional_preds_df.index ==
```

In [30]:
```
forecasted_values = []

for item in list(top_regions['RegionID']):
    forecasted_values.append(get_2019_forecast(item))
```

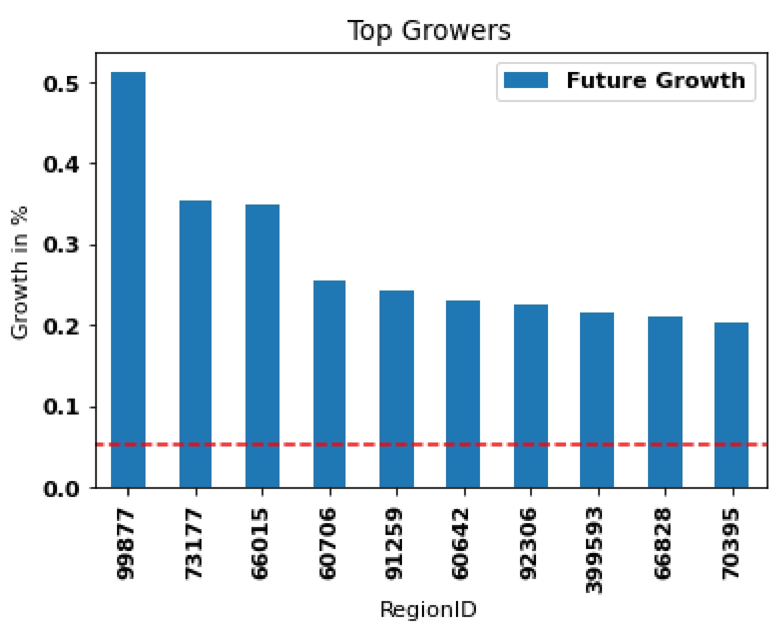
In [31]:
```
#Isolating top regions by forecast

top_future_regions = pd.DataFrame(forecasted_values)

top_future_regions.columns = ['RegionID', '2019 value']

top_100_forecasted_growth = top_future_regions.merge(growth_table, how=

top_100_forecasted_growth['Future Growth'] = (top_100_forecasted_growth
                                              top_100_forecasted_growth

#Isolating Top 10 Growers

top_10_growers_df = top_100_forecasted_growth.sort_values('Future Growt

top_10_growers = top_100_forecasted_growth.sort_values('Future Growth',

top_10_growers = list(top_10_growers['RegionID'])

top_10_growers
```

Out[31]: [99877, 73177, 66015, 60706, 91259, 60642, 92306, 399593, 66828, 70395]

In [51]:
```
avg_growth = np.average(top_100_forecasted_growth['Future Growth'])
```

In [75]:
```
top_10_growers_df.plot(x='RegionID', y='Future Growth', kind='bar')
plt.hlines(avg_growth, xmin=-1, xmax=50, linestyles='dashed', color='re
plt.title('Top Growers')
plt.ylabel('Growth in %')
```

Out[75]: Text(0, 0.5, 'Growth in %')



In [32]:
```
def region_acc_compute(ID, choice):

    region_df = region_melt[region_melt['RegionID'] == ID]

    region_df['time'] = pd.to_datetime(region_df['time'])

    region_df.set_index('time', inplace = True)

    region_df = region_df[['value']]

    X_train = region_df.head(265-12)
    y_train = region_df.tail(12)

    regional_model = statsmodels.tsa.statespace.sarimax.SARIMAX(X_train
                                                  order = best_pdq,
                                                  seasonal_order = best_PDQS,
                                                  enforce_stationarity = False
                                                  enforce_invertibility = Fals

    fit_model = regional_model.fit()
    preds = fit_model.get_forecast(steps = 12).summary_frame()['mean']

    mae = mean_absolute_error(preds, y_train)
    comp_error = round(float(mae / preds[-1:]), 2)

    if choice == 'stats':

        return [ID, mae, comp_error]

    else:

        return preds
```

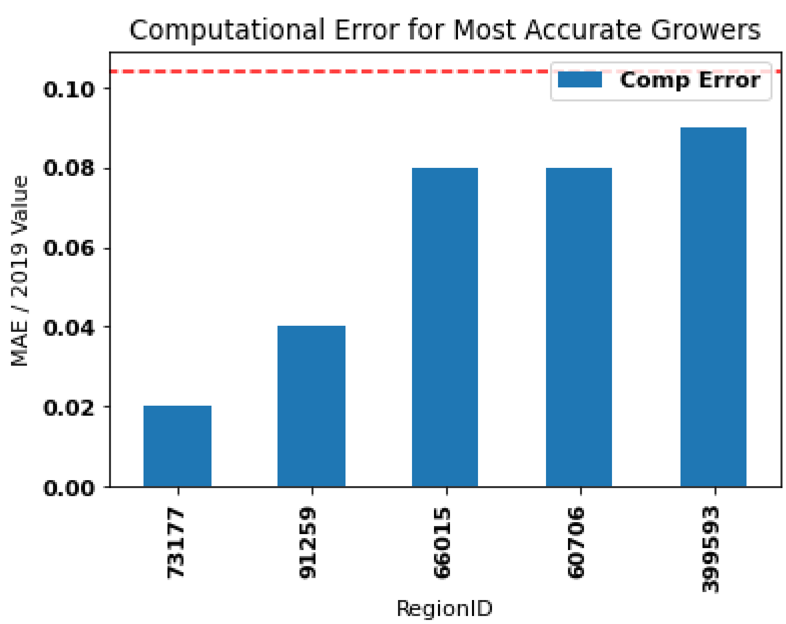
In [34]:
```
region_acc_df = []

for item in top_10_growers:
    region_acc_df.append(region_acc_compute(item, 'stats'))

```

In [42]:
```
#Top 10 Most Accurate

region_acc_df = pd.DataFrame(region_acc_df)

region_acc_df.columns = ['RegionID', 'MAE', 'Comp Error']

most_accurate_growers = region_acc_df.sort_values(by='Comp Error', asce

most_accurate_growers

#Add Descriptors to Region

most_accurate_growers = most_accurate_growers.merge(region_melt, how='i

most_accurate_growers = most_accurate_growers[['RegionID', 'City', 'Sta

most_accurate_growers

most_accurate_growers.to_excel('acc_growers.xlsx')
```

In [81]:
```
comp_error_avg = np.average(region_acc_df['Comp Error'])
```

In [85]:
```
most_accurate_growers.plot('RegionID', 'Comp Error', kind='bar')

plt.hlines(comp_error_avg, xmin=-1, xmax=50, linestyles='dashed', color
plt.ylabel('MAE / 2019 Value')
plt.title('Computational Error for Most Accurate Growers')

```

Out[85]:
```
Text(0.5, 1.0, 'Computational Error for Most Accurate Growers')
```



In [37]:

```
#Create function to plot each forecast

def plot_top_growers(region):

    test_preds = region_acc_compute(region, 'preds')

    sample_region_df = region_melt[region_melt['RegionID'] == region]

    sample_region_df['time'] = pd.to_datetime(sample_region_df['time'])

    sample_region_df.set_index('time', inplace = True)

    sample_region_df = sample_region_df['value']

    y_train_sample_df = sample_region_df.tail(12)

    figure(figsize=(12, 6), dpi=80)

    plt.plot(sample_region_df['2015':], color='black')
    plt.plot(test_preds, color='blue')
    plt.plot(y_train_sample_df='green')

#     county = most_accurate_growers[most_accurate_growers['RegionID']=
#     city = most_accurate_growers[most_accurate_growers['RegionID']==r
#     state = most_accurate_growers[most_accurate_growers['RegionID']==

    location = f'{region}'

    plt.title(f'Forecast For {location}')

    test_preds.to_csv(f'{region}_preds.csv')
```

In [38]:
```
#plot top growers to determine accuracy

for item in list(most_accurate_growers['RegionID']):
    plot_top_growers(item)
```

```
/Users/angelogayanelo/opt/anaconda3/lib/python3.8/site-packages/statsmode
ls/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was
provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
/Users/angelogayanelo/opt/anaconda3/lib/python3.8/site-packages/statsmode
ls/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was
provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
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ls/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was
provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
/Users/angelogayanelo/opt/anaconda3/lib/python3.8/site-packages/statsmode
ls/tsa/base/tsa_model.py:524: ValueWarning: No frequency information was
provided, so inferred frequency MS will be used.
  warnings.warn('No frequency information was'
/Users/angelogayanelo/opt/anaconda3/lib/python3.8/site-packages/statsmode
ls/base/model.py:566: ConvergenceWarning: Maximum Likelihood optimization
failed to converge. Check mle_retvals
```

Step 6: Interpreting Results

In [ ]:
```

```

In [ ]:
```

```