In [1]:

```
import pandas as pd
import numpy as np
from IPython.display import display, Latex
import random
from statsmodels.tsa.ar_model import AutoReg
import matplotlib.pyplot as plt
import datetime
from sklearn.metrics import mean_squared_error
from scipy.fft import fft, ifft, fftfreq


import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning, ModelWarning
warnings.simplefilter('ignore', ConvergenceWarning)
warnings.simplefilter('ignore', ModelWarning)
warnings.simplefilter('ignore')
```

In [37]:

```
from statsmodels.stats.diagnostic import acorr_ljungbox
from statsmodels.tsa.stattools import adfuller, kpss
from statsmodels.tsa.stattools import acf, pacf
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.arima.model import ARIMA
```

MY_MA

In [64]:

```
class myMA:
    def __init__(self, c, thetas):
        self.c = c
        self.thetas = thetas
        self.eps = 0.8
        self.burnIn = 0
        self.order = len(thetas)
        self.y = []
        self.y_cut = []
        self.epsilons = None
        self.autoCor = None
        self.pAutoCor = None
        self.name = self.getEquationStr()

    def predictMany(self, t):
        self.y = np.zeros(t)
        self.epsilons = np.random.normal(0, 1, size = t + self.order)

        # set the other elements
        for i in np.arange(0, t):
            self.y[i] = self.c + self.epsilons[i+self.order]
            for j in range(0, self.order):
                self.y[i] += self.epsilons[i + self.order - (j+1)] * self.thetas[j]

        # check autocorrelation
        _, ax = plt.subplots(4, figsize = (20,8))
        #ax[0].set_xlabel('time')

        timeCorr = 40#(len(self.y) - 1)//10
        self.autoCor = acf(self.y, nlags = timeCorr, fft = True)
        self.pAutoCor = pacf(self.y, nlags= timeCorr)
        #print(self.pAutoCor)
        # determine burnin
        self.burnin()
```

```
        plot_acf(self.y, ax=ax[1], lags = timeCorr, fft = True, zero = False)
        plot_pacf(self.y, ax=ax[2], lags = timeCorr)

        ax[0].plot(self.y)
        ax[0].set_title(f'Autoregressive model ${self.name}$ with T={len(self.y)}, burnI
n={self.burnIn}')
        ax[3].plot(self.y_cut)
        ax[3].set_title(f'Burnin cut')


        #self.burnin()
    # http://sbfnk.github.io/mfiidd/mcmc_diagnostics.html#33_burn-in
    def tests(self, data):
        # jung - box - whether we are dealing with white noise
        # with hypothesis of stationary ts we look at p_value - close to one - uncorrelat
ed - up to lags
        jung = acorr_ljungbox(data, lags = [40], return_df=True)
        print("\n\t\t->jung_test (p_value close to 1 -> uncorrelated):\n\n", jung)

        # augumented Dickey_Fuller test
        # wheather we are dealing with stationary or not
        fuller = adfuller(data) # timeseries in non-stationary
        print("\n\t\t->adfuller (p_value close to 0 -> stationary):\n\n",fuller)
        # if p value is small - > it is stationary

        #kwiatkowski-phillips-s.. test - > hyphothesis is that it is stationary -> p_valu
e high -> stationary
        kp = kpss(data)
        print("\n\t\t->kpss (p_value close to 1 -> stationary):\n\n",kp)

    def burnin(self):

        print("\n\n\t->test before:")
        self.tests(self.y)
        val = np.exp(-1/self.eps)
        for i in range(len(self.autoCor)):
            autocor = abs(self.autoCor[i])
            #print(autocor)
            if autocor < val:
                self.burnIn = i
                break
        self.y_cut = self.y[self.burnIn:-1]
        print("\n\n\t->test after:")
        self.tests(self.y_cut)
        print(f'\n\t->Burnin parameter is {self.burnIn}')

    def getEquationStr(self):
        eq = f'y_t={self.c}'
        inside = str([f'{"+" if val > 0 else ""}{val:.2f}'+'y_{t-%s}'%(str(t+1)) for t,
val in enumerate(self.thetas)]).replace('\'[]','')
        for k in ['\'', '[', ']']:
            inside = inside.replace(k,'')
        eq += inside
        eq += '+e_t'
        display(Latex(f" --------------------------------- Doing AR({len(self.y)}): ${eq
}$ --------------------------------- "))
        return  eq
```

first 0.8

In [65]:

```
c = 20
phi = [0.8]
a = myMA(c, phi)
a.predictMany(5000)
```

--------------------------------- Doing AR(0): $y_t = 20 + 0.80 y_{t-1} + e_t$ **---------------------------------**

->test before:

->test before:

  ->jung_test (p_value close to 1 -> uncorrelated):

```
        lb_stat      lb_pvalue
40  1248.567212  8.272511e-236
```

  ->adfuller (p_value close to 0 -> stationary):

 (-18.240737823678348, 2.3552827517304848e-30, 14, 4985, {'1%': -3.4316624715142177, '5%': -2.862119970102166, '10%': -2.5670787188546584}, 14075.074531407974)

  ->kpss (p_value close to 1 -> stationary):

 (0.1067282649779246, 0.1, 32, {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})

 ->test after:

  ->jung_test (p_value close to 1 -> uncorrelated):

```
        lb_stat      lb_pvalue
40  1249.307702  5.777318e-236
```

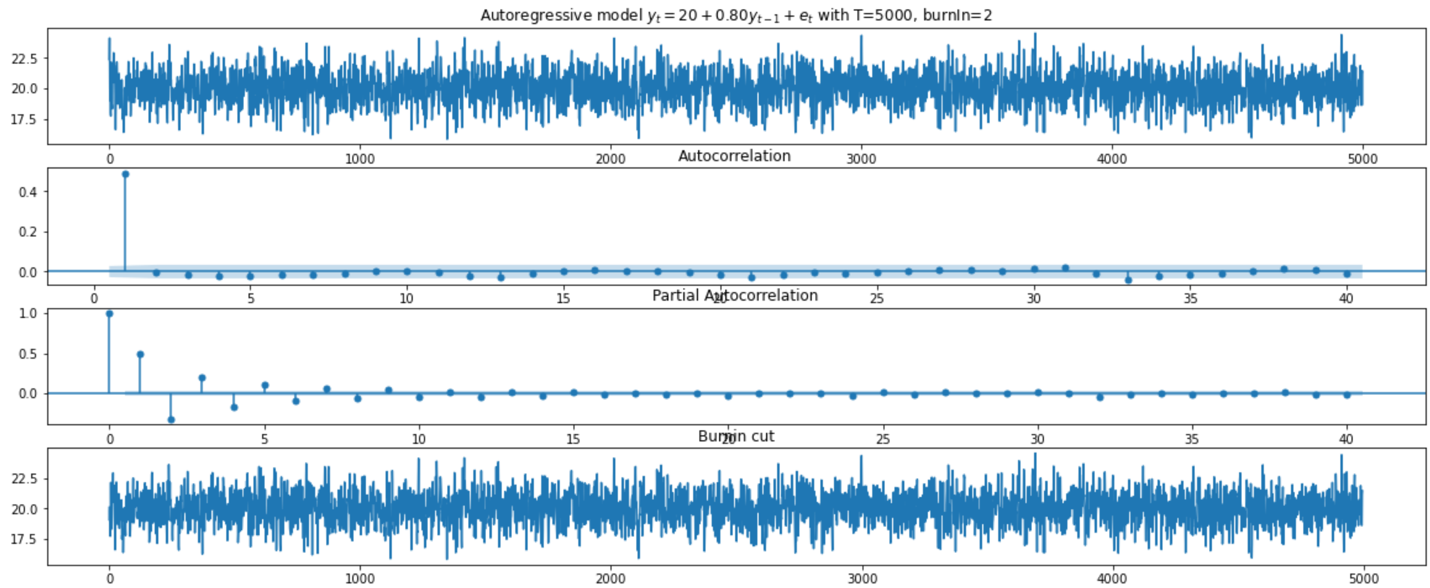
  ->adfuller (p_value close to 0 -> stationary):

 (-18.245881811059668, 2.349048983173022e-30, 14, 4982, {'1%': -3.4316632622500816, '5%': -2.8621203194445384, '10%': -2.5670789048233216}, 14067.025030903353)

  ->kpss (p_value close to 1 -> stationary):

 (0.10044307319464742, 0.1, 32, {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})

 ->Burnin parameter is 2



second -1, 0.8

In [66]:

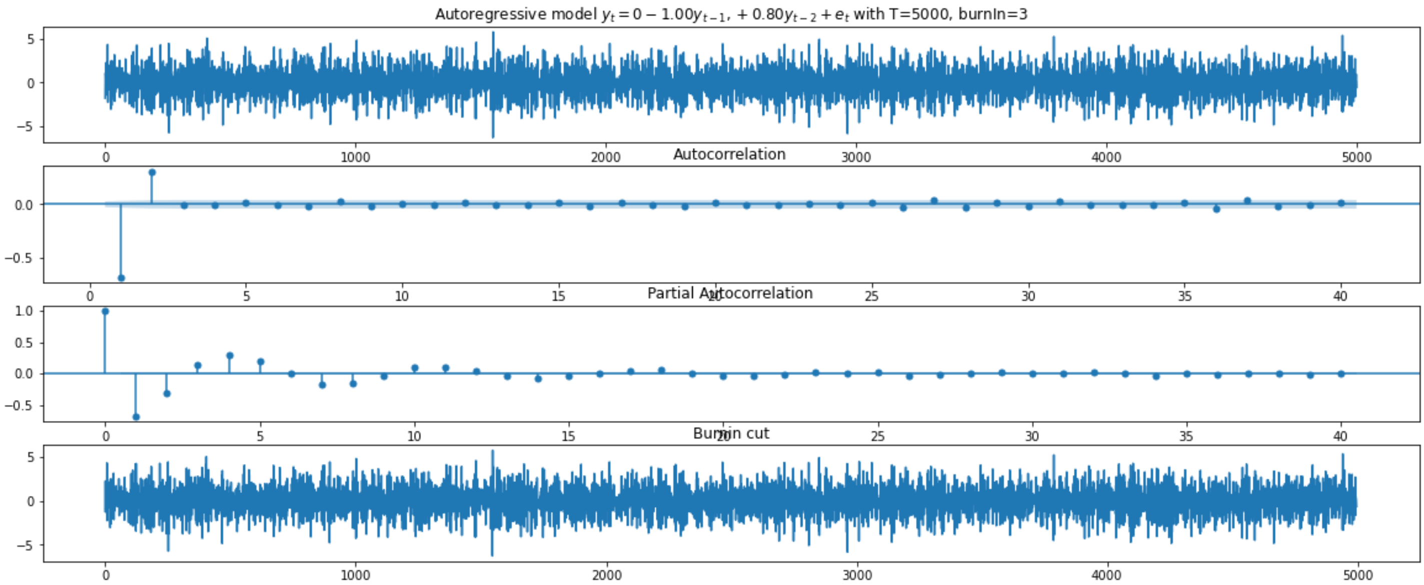
```
c = 0
phi = [-1, 0.8]
a = myMA(c, phi)
a.predictMany(5000)
```

-------------------------------- Doing AR(0): $y_t = 0 - 1.00y_{t-1}, +0.80y_{t-2} + e_t$ **--------------------------------**

 ->test before:

  ->jung_test (p_value close to 1 -> uncorrelated):

```
         lb_stat  lb_pvalue
40  2903.747019        0.0

  ->adfuller (p_value close to 0 -> stationary):

 (-12.970216768261565, 3.092448677492304e-24, 28, 4971, {'1%': -3.431666169784722, '5%':
-2.862121603975143, '10%': -2.567079588629541}, 14127.1437833252)

  ->kpss (p_value close to 1 -> stationary):

 (0.04488214866944349, 0.1, 32, {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})


 ->test after:

  ->jung_test (p_value close to 1 -> uncorrelated):

         lb_stat  lb_pvalue
40  2903.529099        0.0

  ->adfuller (p_value close to 0 -> stationary):

 (-12.845260355869103, 5.497567861341495e-24, 28, 4967, {'1%': -3.4316672302646283, '5%':
-2.8621220724882153, '10%': -2.5670798380375506}, 14119.041268320798)

  ->kpss (p_value close to 1 -> stationary):

 (0.0437708406815965, 0.1, 32, {'10%': 0.347, '5%': 0.463, '2.5%': 0.574, '1%': 0.739})

 ->Burnin parameter is 3
```



In [81]:

```python
model = ARIMA(a.y, order = (0, 0, 2))
results = model.fit()
pred = results.predict(dynamic = False)

_, ax = plt.subplots(1, figsize = (20,2))
ax.plot(a.y, alpha = 0.3)
ax.plot(pred)
results.summary()
```

Out[81]:

SARIMAX Results

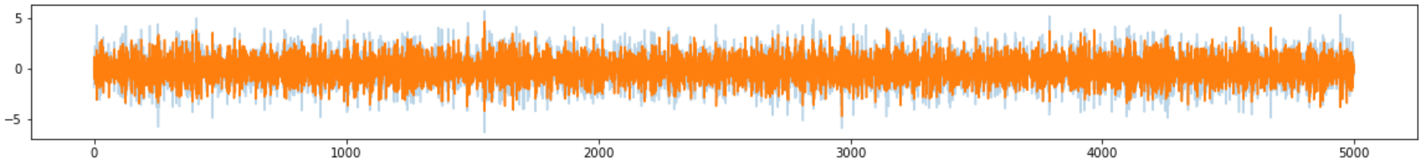
Dep. Variable:	y	**No. Observations:**	5000
Model:	ARIMA(0, 0, 2)	**Log Likelihood**	-7097.369
Date:	Tue, 26 Apr 2022	**AIC**	14202.739
Time:	08:17:17	**BIC**	14228.807

Sample:	0	**HQIC**	14211.875
	- 5000		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	0.0013	0.011	0.116	0.908	-0.021	0.023
ma.L1	-1.0081	0.009	-115.320	0.000	-1.025	-0.991
ma.L2	0.7994	0.008	94.723	0.000	0.783	0.816
sigma2	1.0006	0.021	48.498	0.000	0.960	1.041

Ljung-Box (L1) (Q):	0.01	**Jarque-Bera (JB):**	4.54
Prob(Q):	0.92	**Prob(JB):**	0.10
Heteroskedasticity (H):	0.96	**Skew:**	-0.05
Prob(H) (two-sided):	0.40	**Kurtosis:**	2.89

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



AR FORECASTING

In [3]:

```
from statsmodels.tsa.ar_model import AR, ARResults
def printAR(fit):
    print(f'Lag:\n\t{fit.k_ar}\ncoeff:\n{fit.params}')

def reverseDiff(df, diff, column, shift = 1):
    x, x_diff = df[column].iloc[0], diff.iloc[shift:]
    return pd.Series(np.r_[x, x_diff].cumsum())

shift = 1
maxlag = 20
```

In [390]:

```
robusta = pd.read_html('https://www.indexmundi.com/commodities/?commodity=robusta-coffee&
months=240')
robustaDF = robusta[1]
robustaDF['Month'] = pd.to_datetime(robustaDF['Month'])
robustaDF.set_index(['Month'], inplace = True)
robustaDF
```

Out[390]:

	Price	Change
Month		
2002-03-01	0.64	-
2002-04-01	0.65	1.56%
2002-05-01	0.62	-4.62%
2002-06-01	0.63	1.61%
2002-07-01	0.63	0.00%

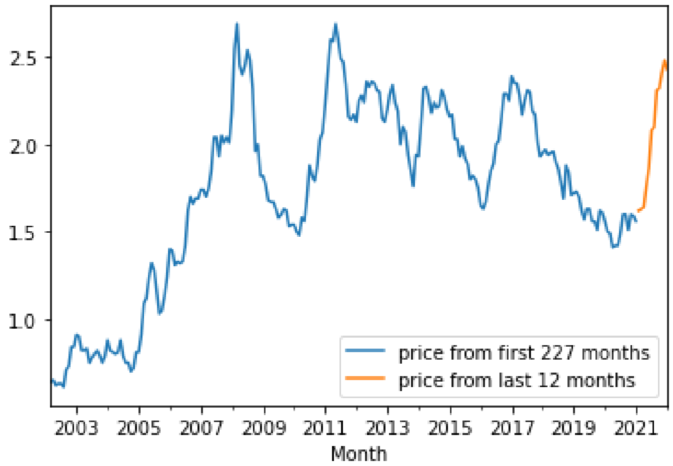
Month	Price	Change
...	...	...
2021-09-01	2.31	10.00%
2021-10-01	2.32	0.43%
2021-11-01	2.41	3.88%
2021-12-01	2.48	2.90%
2022-01-01	2.43	-2.02%

239 rows × 2 columns

Train-Test split

In [391]:

```
forecastLen = 12
trainLen = len(robustaDF)-forecastLen

trainRobusta = robustaDF.iloc[:trainLen]
testRobusta = robustaDF.iloc[trainLen:]
trainRobusta.columns = [f'price from first {len(robustaDF)-forecastLen} months', 'Change
']
testRobusta.columns = [f'price from last {forecastLen} months', 'Change']
ax = trainRobusta.plot()
testRobusta.plot(ax=ax, label = f'last {forecastLen} months', legend = True)


columnTrain = trainRobusta.columns[0]
columnTest = testRobusta.columns[0]
```



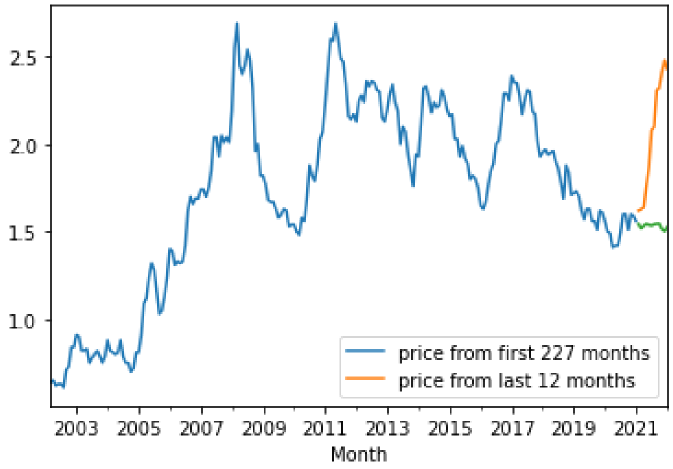
Non-differenced data

In [392]:

```
modelNon = AR(trainRobusta[columnTrain])
# fit
fitNon = modelNon.fit(maxlag = maxlag, method = 'mle')
printAR(fitNon)
# predict
start = len(trainRobusta)
end = len(trainRobusta) + len(testRobusta) - 1
predNon = fitNon.predict(start = start, end = end, dynamic = False).rename('Non differen
ced data')

ax = trainRobusta.plot()
testRobusta.plot(ax=ax)
predNon.plot(ax=ax)
accNon = mean_squared_error(testRobusta[columnTest].to_numpy(), predNon.to_numpy())
print(f"The accuracy is - mse = {accNon}")
```

Lag:

```
Lag:
 20
coeff:
const                               0.024078
L1.price from first 227 months      1.250700
L2.price from first 227 months     -0.263838
L3.price from first 227 months      0.008547
L4.price from first 227 months      0.006578
L5.price from first 227 months      0.012330
L6.price from first 227 months     -0.012362
L7.price from first 227 months     -0.064562
L8.price from first 227 months      0.066119
L9.price from first 227 months      0.042034
L10.price from first 227 months    -0.062886
L11.price from first 227 months    -0.069081
L12.price from first 227 months     0.064803
L13.price from first 227 months     0.014477
L14.price from first 227 months     0.087147
L15.price from first 227 months    -0.233665
L16.price from first 227 months     0.083275
L17.price from first 227 months     0.141037
L18.price from first 227 months    -0.160210
L19.price from first 227 months     0.172394
L20.price from first 227 months    -0.098393
dtype: float64
The accuracy is - mse = 0.3790813009420537
```



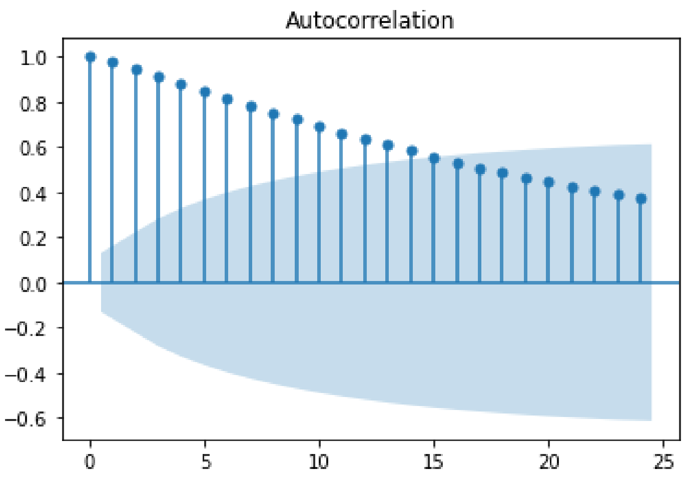
Differenced data

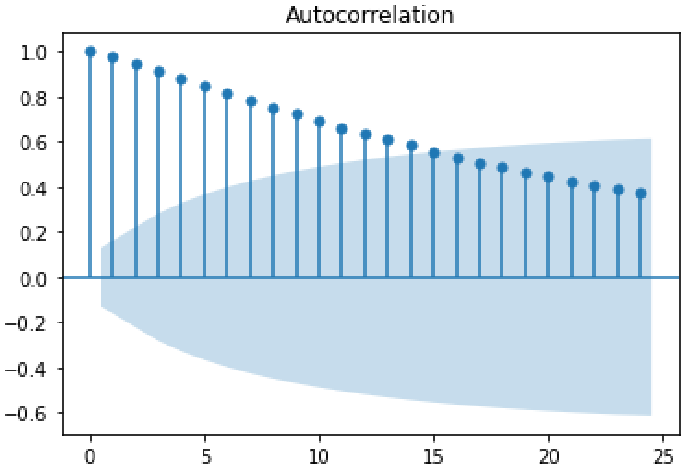
check the autocorrelation

In [393]:

```
plot_acf(trainRobusta[columnTrain])
```

Out[393]:





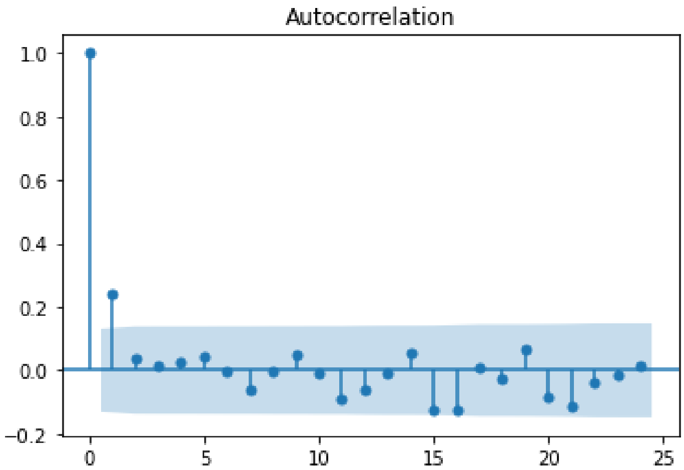
create difference

In [394]:

```
trainRobustaDiff = trainRobusta[columnTrain].diff(shift).dropna()
plot_acf(trainRobustaDiff)
trainRobustaDiff
```

Out[394]:

```
Month
2002-04-01    0.01
2002-05-01   -0.03
2002-06-01    0.01
2002-07-01    0.00
2002-08-01   -0.02
              ...
2020-09-01    0.00
2020-10-01   -0.09
2020-11-01    0.09
2020-12-01   -0.01
2021-01-01   -0.03
Name: price from first 227 months, Length: 226, dtype: float64
```



fit again

In [397]:

```
model = AR(trainRobustaDiff.to_numpy())
# fit
fit = model.fit(maxlag = maxlag, method = 'mle')
printAR(fit)
# predict
start = len(trainRobustaDiff)  #+ diff
end = len(trainRobustaDiff) + len(testRobusta) - 1
pred = fit.predict(start = start, end = end, dynamic = False)
```

```
pred = pd.Series(pred, index = testRobusta.index)

fullDifferencedPred = trainRobusta[columnTrain].diff(shift).append(pred, ignore_index=True)
# return to non-differenced data
diffBack = reverseDiff(trainRobusta, trainRobusta[columnTrain].diff(shift), columnTrain, shift)
predReal = reverseDiff(trainRobusta, fullDifferencedPred, columnTrain, shift)

full = pd.DataFrame(columns=['real','diff', 'back'])
full['diff'] = trainRobustaDiff
full['real'] = trainRobusta[columnTrain].iloc[shift:]
full['back'] = diffBack.iloc[shift:].to_numpy()

#"print(predReal)
predReal = pd.Series(predReal[shift:].to_numpy(), index = robustaDF.index[1:])
predRealTest = pd.DataFrame(columns=['pred','real'])
predRealTest['differenced'] = predReal.to_numpy()
predRealTest['real'] = robustaDF['Price'].iloc[shift:].to_numpy()
predRealTest.index = robustaDF.index[shift:]
predRealTest
```

```
Lag:
 20
coeff:
[ 0.00373972  0.26837138 -0.01840859  0.00919475 -0.00051124  0.0018554
  0.01896558 -0.05591133  0.00854913  0.04430708 -0.01044202 -0.07185736
 -0.01494307 -0.00477558  0.08858318 -0.14371465 -0.0616476   0.07925602
 -0.08342745  0.12026067 -0.11652976]
```

Out[397]:

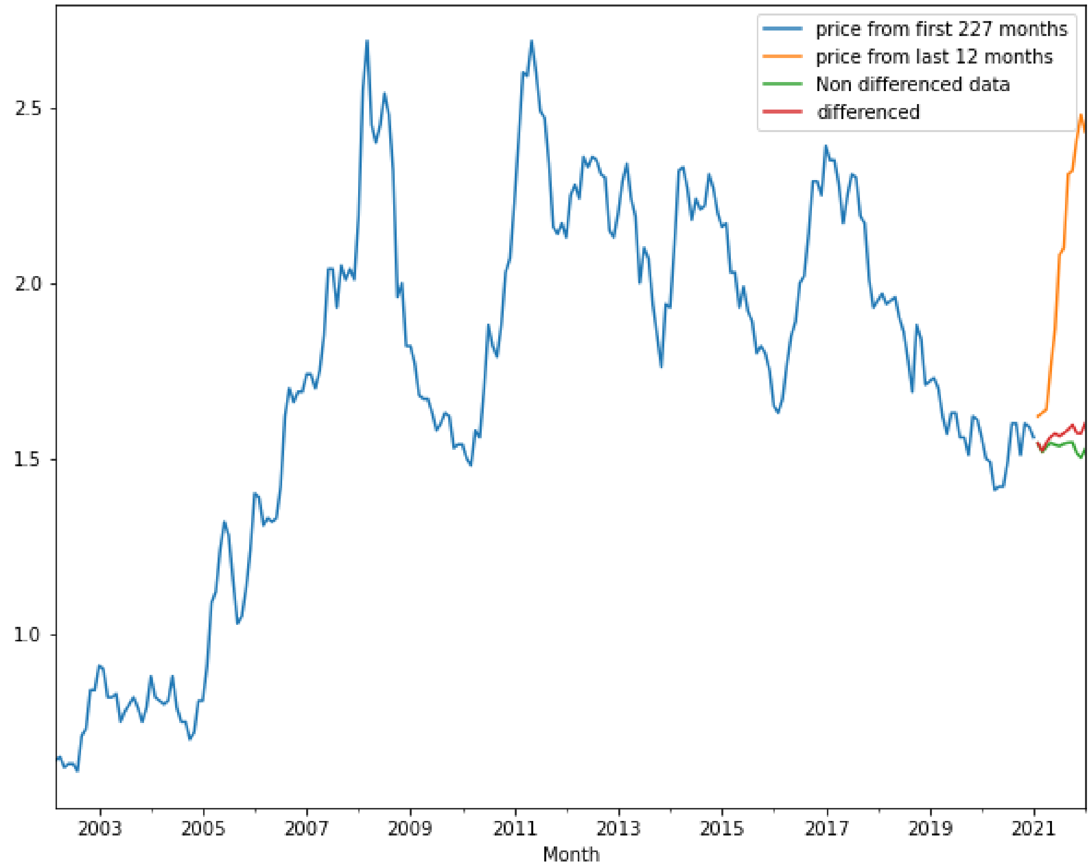
	pred	real	differenced
Month			
2002-04-01	NaN	0.65	0.650000
2002-05-01	NaN	0.62	0.620000
2002-06-01	NaN	0.63	0.630000
2002-07-01	NaN	0.63	0.630000
2002-08-01	NaN	0.61	0.610000
...	...	...	...
2021-09-01	NaN	2.31	1.582145
2021-10-01	NaN	2.32	1.596471
2021-11-01	NaN	2.41	1.572697
2021-12-01	NaN	2.48	1.571715
2022-01-01	NaN	2.43	1.600881

238 rows × 3 columns

In [398]:

```
# compare all predictions
fig, ax = plt.subplots(1, figsize = (10,8))
# plot just the training
trainRobusta[columnTrain].plot(ax = ax)
# plot real data from last part
testRobusta[columnTest].plot(ax = ax)
#ax.plot(testRobusta.index, np.array(testRobusta[columnTest]), label = 'original data')
# plot non-differenced prediction
predNon.plot(ax=ax)
# plot differenced prediction
#ax.plot(testRobusta.index, predNon.diff(), label = 'non-differenced data predicted')
predRealTest.iloc[trainLen-shift:]['differenced'].plot(ax=ax)
#ax.plot(testRobusta.index, pred, label = 'differenced data predicted')
ax.legend()
```

```
plt.show()

#accNon = mean_squared_error(testRobusta[columnTest].diff().to_numpy(), predNon.to_numpy(
))
print(f"The accuracy is - mse = {accNon}")
#testRobusta.index, pred
```




```
The accuracy is - mse = 0.3790813009420537
```

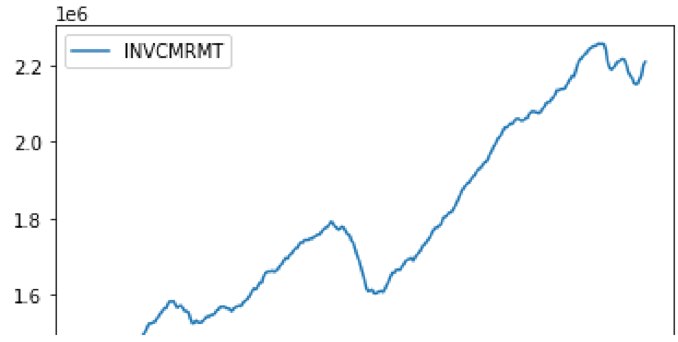
TRY IT WITH ARIMA MODEL

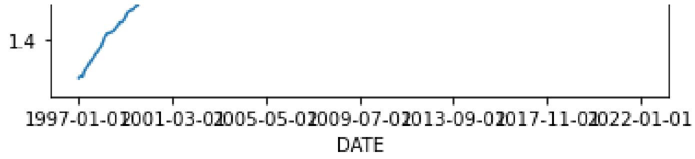
In [70]:

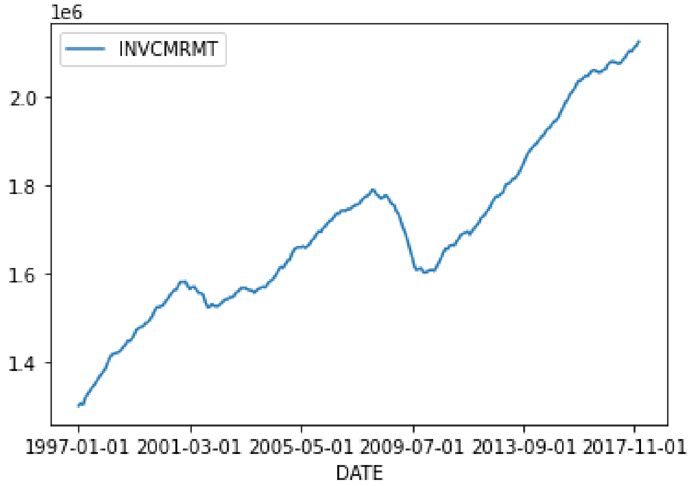
```
df = pd.read_csv('INVCMRMT.csv', parse_dates = True)
df = df.set_index('DATE')
df.plot()

# set the dates
timestart = datetime.datetime(1997,1,1)
timeend = datetime.datetime(2018,1,1)
df_train = df.loc['1997-01-01':'2018-01-01']
df_train.plot()
df_test = df.loc['2018-01-01':]
df_test.plot()
```

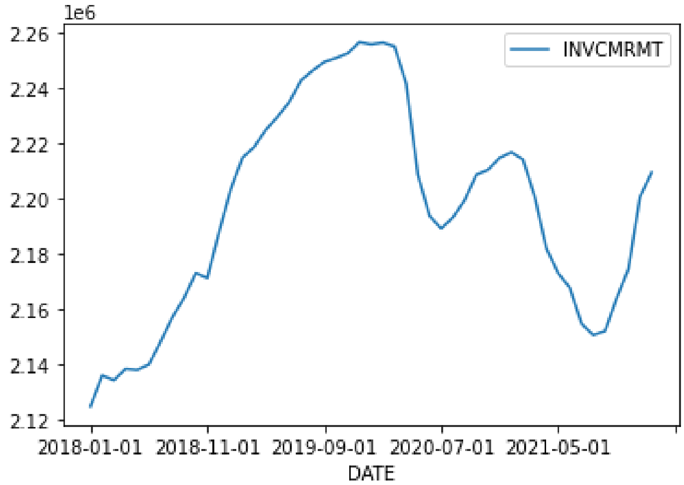
Out[70]:

```
<AxesSubplot:xlabel='DATE'>
```









In [27]:

```
df_test
```

Out[27]:

	INVCMRMT
DATE	
2018-01-01	2124655.0
2018-02-01	2135865.0
2018-03-01	2134146.0
2018-04-01	2138236.0
2018-05-01	2137865.0
2018-06-01	2139842.0
2018-07-01	2148096.0
2018-08-01	2156969.0
2018-09-01	2163820.0
2018-10-01	2172890.0
2018-11-01	2171104.0
2018-12-01	2187849.0
2019-01-01	2203273.0
2019-02-01	2214705.0

DATE	INVCMRMT
2019-03-01	[illegible]
2019-04-01	2224743.0
2019-05-01	2229532.0
2019-06-01	2234770.0
2019-07-01	2242688.0
2019-08-01	2246188.0
2019-09-01	2249368.0
2019-10-01	2250747.0
2019-11-01	2252485.0
2019-12-01	2256493.0
2020-01-01	2255686.0
2020-02-01	2256314.0
2020-03-01	2254999.0
2020-04-01	2241518.0
2020-05-01	2208616.0
2020-06-01	2193622.0
2020-07-01	2189018.0
2020-08-01	2193103.0
2020-09-01	2199245.0
2020-10-01	2208535.0
2020-11-01	2210256.0
2020-12-01	2214628.0
2021-01-01	2216700.0
2021-02-01	2213991.0
2021-03-01	2200458.0
2021-04-01	2181829.0
2021-05-01	2172823.0
2021-06-01	2167664.0
2021-07-01	2154586.0
2021-08-01	2150445.0
2021-09-01	2151906.0
2021-10-01	2163742.0
2021-11-01	2174279.0
2021-12-01	2200521.0
2022-01-01	2209308.0

In [71]:

```
from statsmodels.tsa.statespace.sarimax import SARIMAX
from statsmodels.tsa.seasonal import seasonal_decompose
from pmdarima import auto_arima

import warnings
from statsmodels.tools.sm_exceptions import ConvergenceWarning, ModelWarning
warnings.simplefilter('ignore', ConvergenceWarning)
warnings.simplefilter('ignore', ModelWarning)
warnings.simplefilter('ignore')

from sklearn.metrics import mean_squared_error, mean_absolute_percentage_error
auto_arima(df, seasonal = False, m = 2, trace = True).summary()
```

```
Performing stepwise search to minimize aic
 ARIMA(2,1,2)(0,0,0)[0] intercept   : AIC=6202.069, Time=0.30 sec
 ARIMA(0,1,0)(0,0,0)[0] intercept   : AIC=6163.739, Time=0.01 sec
 ARIMA(1,1,0)(0,0,0)[0] intercept   : AIC=6239.111, Time=0.03 sec
 ARIMA(0,1,1)(0,0,0)[0] intercept   : AIC=6169.342, Time=0.04 sec
 ARIMA(0,1,0)(0,0,0)[0]             : AIC=6213.779, Time=0.01 sec
 ARIMA(1,1,1)(0,0,0)[0] intercept   : AIC=6209.402, Time=0.08 sec

Best model:  ARIMA(0,1,0)(0,0,0)[0] intercept
Total fit time: 0.474 seconds
```

Out[71]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	301
Model:	SARIMAX(0, 1, 0)	**Log Likelihood**	-3079.870
Date:	Tue, 26 Apr 2022	**AIC**	6163.739
Time:	08:13:02	**BIC**	6171.147
Sample:	0	**HQIC**	6166.704
	- 301		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	3027.1567	478.019	6.333	0.000	2090.258	3964.056
sigma2	4.838e+07	2.86e+06	16.941	0.000	4.28e+07	5.4e+07

Ljung-Box (L1) (Q):	117.91	**Jarque-Bera (JB):**	226.16
Prob(Q):	0.00	**Prob(JB):**	0.00
Heteroskedasticity (H):	1.93	**Skew:**	-1.26
Prob(H) (two-sided):	0.00	**Kurtosis:**	6.42

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

In [69]:

```
model = ARIMA(df_train, order = (0, 0, 2))
results = model.fit()
results.summary()
```

Out[69]:

SARIMAX Results

Dep. Variable:	INVCMRMT	**No. Observations:**	253
Model:	ARIMA(0, 0, 2)	**Log Likelihood**	-3321.590
Date:	Tue, 26 Apr 2022	**AIC**	6651.181
Time:	08:12:31	**BIC**	6665.314
Sample:	01-01-1997	**HQIC**	6656.867
	- 01-01-2018		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
const	1.697e+06	1.68e+05	10.118	0.000	1.37e+06	2.03e+06
ma.L1	1.7630	0.656	2.689	0.007	0.478	3.048
ma.L2	0.8883	0.662	1.341	0.180	-0.410	2.187

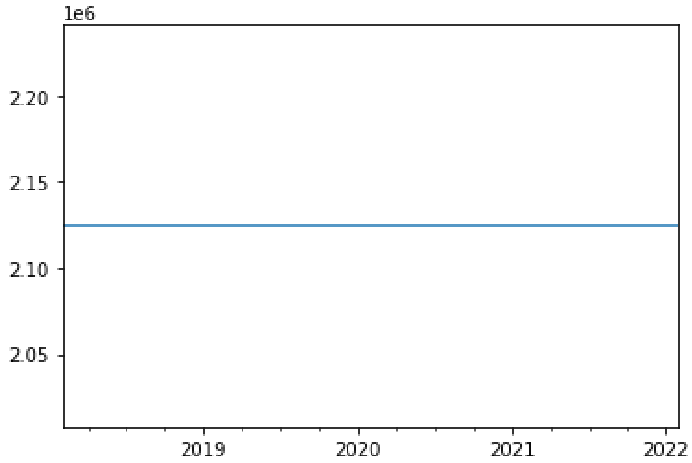
sigma2	3.617e+10	0.068	5.32e+11	0.000	3.62e+10	3.62e+10

Ljung-Box (L1) (Q):	203.44	**Jarque-Bera (JB):**	3.72
Prob(Q):	0.00	**Prob(JB):**	0.16
Heteroskedasticity (H):	1.39	**Skew:**	0.28
Prob(H) (two-sided):	0.14	**Kurtosis:**	2.81

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 1.62e+28. Standard errors may be unstable.

In [36]:

```
start = len(df_train)
end = start + len(df_test) - 1
predictions = results.predict(start = start, end = end, dynamic=False, typ='levels').ren
ame('SARIMA(0,1,0)(0,0,0,2)')
ax = predictions.plot()
#df_train.plot(ax=ax)
#df_test.plot(ax=ax)
#mean_absolute_percentage_error(df_test, predictions)
```



In [ ]: