Importação de Bibliotecas básicas para compreensão dos dados

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
!pip install pmdarima

%matplotlib inline
```

```
Requirement already satisfied: pmdarima in /usr/local/lib/python3.6/dist-packag
es (1.8.0)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.6/dist-package
s (from pmdarima) (1.24.3)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.6/dist-p
ackages (from pmdarima) (1.19.5)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-pa
ckages (from pmdarima) (1.0.0)
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.6/d
ist-packages (from pmdarima) (0.22.2.post1)
Requirement already satisfied: statsmodels!=0.12.0,>=0.11 in /usr/local/lib/pyt
hon3.6/dist-packages (from pmdarima) (0.12.1)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.6/dist-pa
ckages (from pmdarima) (1.1.5)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.6/dist-pa
ckages (from pmdarima) (1.4.1)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/lib/py
thon3.6/dist-packages (from pmdarima) (51.3.3)
Requirement already satisfied: Cython<0.29.18,>=0.29 in /usr/local/lib/python3.
6/dist-packages (from pmdarima) (0.29.17)
Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.6/dist-pack
ages (from statsmodels!=0.12.0,>=0.11->pmdarima) (0.5.1)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-pa
ckages (from pandas>=0.19->pmdarima) (2018.9)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python
3.6/dist-packages (from pandas>=0.19->pmdarima) (2.8.1)
Requirement already satisfied: six in /usr/local/lib/python3.6/dist-packages (f
rom patsy>=0.5->statsmodels!=0.12.0,>=0.11->pmdarima) (1.15.0)
```

In [2]:
```
import warnings
warnings.filterwarnings("ignore")
```

Base de Dados - Receita Tributária Estadual de SP

*Fonte: [https://portal.fazenda.sp.gov.br/acessoinformacao/Paginas/Relat%C3%B3rios-da-Receita-Tribut%C3%A1ria.aspx#](https://portal.fazenda.sp.gov.br/acessoinformacao/Paginas/Relat%C3%B3rios-da-Receita-Tribut%C3%A1ria.aspx) (https://portal.fazenda.sp.gov.br/acessoinformacao/Paginas/Relat%C3%B3rios-da-Receita-Tribut%C3%A1ria.aspx)

In [3]:
```
SP = pd.read_excel('Receita_SP.xlsx', index_col = 'PERIODO', parse_dates=True)
```

In [4]:
```
SP.head()
```

Out[4]:

PERIODO	ICMS	IPVA	ITCMD	TAXAS	total
2004-01-01	3575.1	1445.6	17.6	148.8	5187.1
2004-02-01	3262.9	753.9	15.8	122.1	4154.7
2004-03-01	3469.4	566.5	42.8	146.9	4225.6
2004-04-01	3657.0	146.3	27.4	138.1	3968.7
2004-05-01	3667.4	133.3	29.6	152.8	3983.1

In [5]:
```
SP.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 203 entries, 2004-01-01 to 2020-11-01
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   ICMS    203 non-null    float64
 1   IPVA    203 non-null    float64
 2   ITCMD   203 non-null    float64
 3   TAXAS   203 non-null    float64
 4   total   203 non-null    float64
dtypes: float64(5)
memory usage: 9.5 KB
```

In [6]:
```
receitas = [x for x in SP]
```

- Os dados acima nos mostram mês a mês a **Arrecadação das receitas tributárias do Estado de São Paulo, divido por cada Tributo e seu total**.

- Neste primeiro momento vamos plotar todos estes dados, para vizualiarmos de maneira melhor, e tirar algumas conclusões

In [7]:
```
SP.plot(figsize = (15,8));
```

1. A partir do gráfico é possível observar grande predominio na arrecadação de do Estado de São Paulo vem do ICMS e logo na sequência o IPVA (que gera os picos de arrecadação).

In [8]:
```
soma = {}

for i in SP:
  soma[i] = SP[i].sum()
```

In [9]:
```
soma
```

Out[9]:
```
{'ICMS': 1696680.0,
 'IPVA': 189708.70000000004,
 'ITCMD': 25220.6,
 'TAXAS': 70870.0,
 'total': 1982480.3}
```

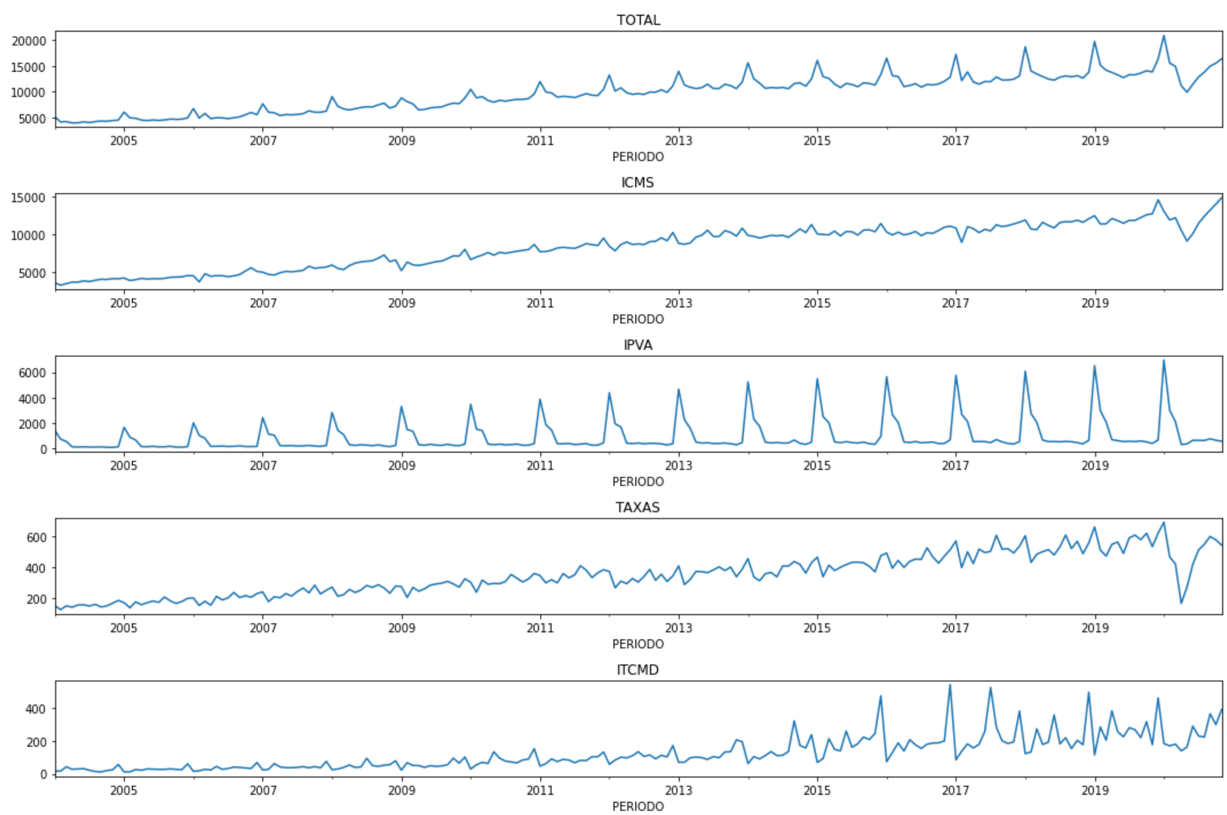
In [10]:
```
soma_pd = pd.DataFrame.from_dict(soma, orient='index', columns=['Soma'])
```

In [11]:
```
soma_pd.sort_values(by='Soma', ascending=False).head(6)
```

Out[11]:

	Soma
total	1982480.3
ICMS	1696680.0
IPVA	189708.7
TAXAS	70870.0
ITCMD	25220.6

In [12]:
```
fig, (ax1,ax2,ax3, ax4, ax5) = plt.subplots(5,1, figsize=(15,10))
SP['total'].plot(ax=ax1, title='TOTAL')
SP['ICMS'].plot(ax=ax2, title='ICMS')
SP['IPVA'].plot(ax=ax3, title='IPVA')
SP['TAXAS'].plot(ax=ax4, title='TAXAS')
SP['ITCMD'].plot(ax=ax5, title='ITCMD')
plt.tight_layout()
```



- É possível observar uma tendência de aumento da receita tributária estadual.
- Como forma de simplificar os estudos, analisaremos a tendência Geral (soma de todos tributos), que já consta na coluna nomeada como **"total"**.
- Analisaremos também o ICMS, Grande responsável pela arrecadação do Estado.

In [13]:
```
# Fazer uma cópia do dataframe para trabalhar

df = SP.copy()
```

In [14]:
```
df.index.freq = 'MS'                    # month start frequency - frequência mensal
# https://pandas.pydata.org/pandas-docs/stable/user_guide/timeseries.html#offset-
```

In [15]:
```
df.head()
```

Out[15]:

	ICMS	IPVA	ITCMD	TAXAS	total
PERIODO					
2004-01-01	3575.1	1445.6	17.6	148.8	5187.1
2004-02-01	3262.9	753.9	15.8	122.1	4154.7
2004-03-01	3469.4	566.5	42.8	146.9	4225.6
2004-04-01	3657.0	146.3	27.4	138.1	3968.7
2004-05-01	3667.4	133.3	29.6	152.8	3983.1

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 203 entries, 2004-01-01 to 2020-11-01
Freq: MS
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   ICMS    203 non-null    float64
 1   IPVA    203 non-null    float64
 2   ITCMD   203 non-null    float64
 3   TAXAS   203 non-null    float64
 4   total   203 non-null    float64
dtypes: float64(5)
memory usage: 9.5 KB
```

In [17]:
```
df.index
```

Out[17]:
```
DatetimeIndex(['2004-01-01', '2004-02-01', '2004-03-01', '2004-04-01',
               '2004-05-01', '2004-06-01', '2004-07-01', '2004-08-01',
               '2004-09-01', '2004-10-01',
               ...
               '2020-02-01', '2020-03-01', '2020-04-01', '2020-05-01',
               '2020-06-01', '2020-07-01', '2020-08-01', '2020-09-01',
               '2020-10-01', '2020-11-01'],
              dtype='datetime64[ns]', name='PERIODO', length=203, freq='MS')
```

In [18]:
```
df.tail()
```

Out[18]:

	ICMS	IPVA	ITCMD	TAXAS	total
PERIODO					
2020-07-01	11478.2	656.6	228.6	511.8	12875.2
2020-08-01	12411.2	642.0	221.8	548.9	13823.9
2020-09-01	13240.2	778.2	363.0	600.0	14981.4
2020-10-01	14027.3	660.2	298.0	577.3	15562.8
2020-11-01	14875.0	589.1	388.8	542.8	16395.6

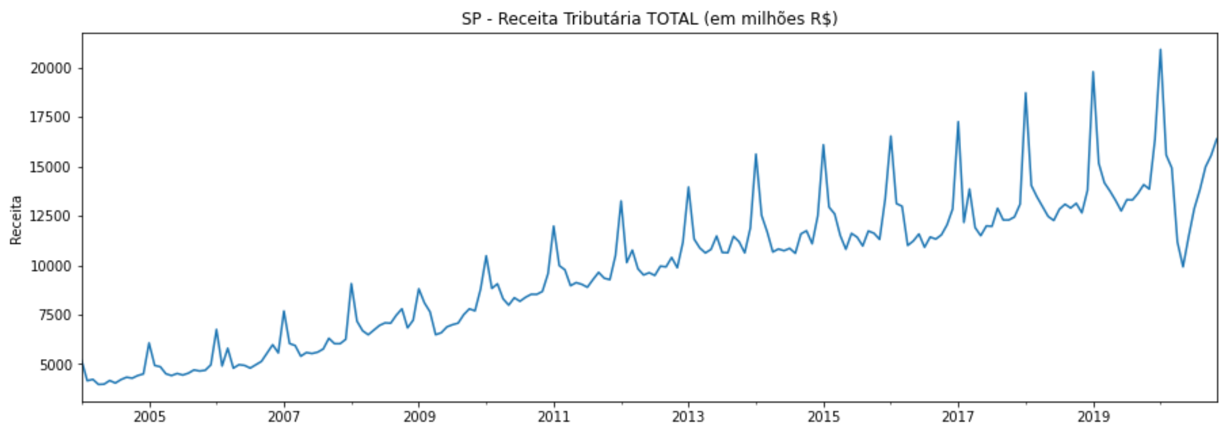
In [19]:
```
df.describe()
```

Out[19]:

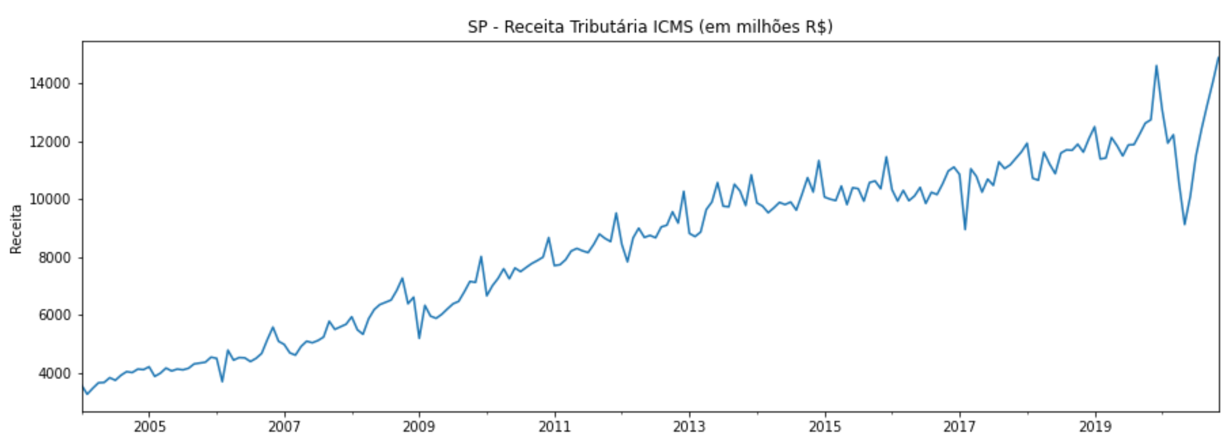
	ICMS	IPVA	ITCMD	TAXAS	total
count	203.000000	203.000000	203.000000	203.000000	203.000000
mean	8358.029557	934.525616	124.239409	349.113300	9765.912808
std	2818.296759	1263.853254	103.617778	133.577133	3537.890161
min	3262.900000	100.700000	11.400000	122.100000	3968.700000
25%	5822.250000	289.700000	44.900000	239.300000	6733.700000
50%	8788.000000	450.900000	94.800000	336.800000	10137.500000
75%	10533.800000	735.450000	178.650000	440.600000	12281.600000
max	14875.000000	6969.100000	540.200000	692.500000	20927.600000

Plotar os Dados

In [20]:
```
title='SP - Receita Tributária TOTAL (em milhões R$)'
ylabel='Receita'
xlabel=''

ax = df['total'].plot(figsize=(15,5),title=title);
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```

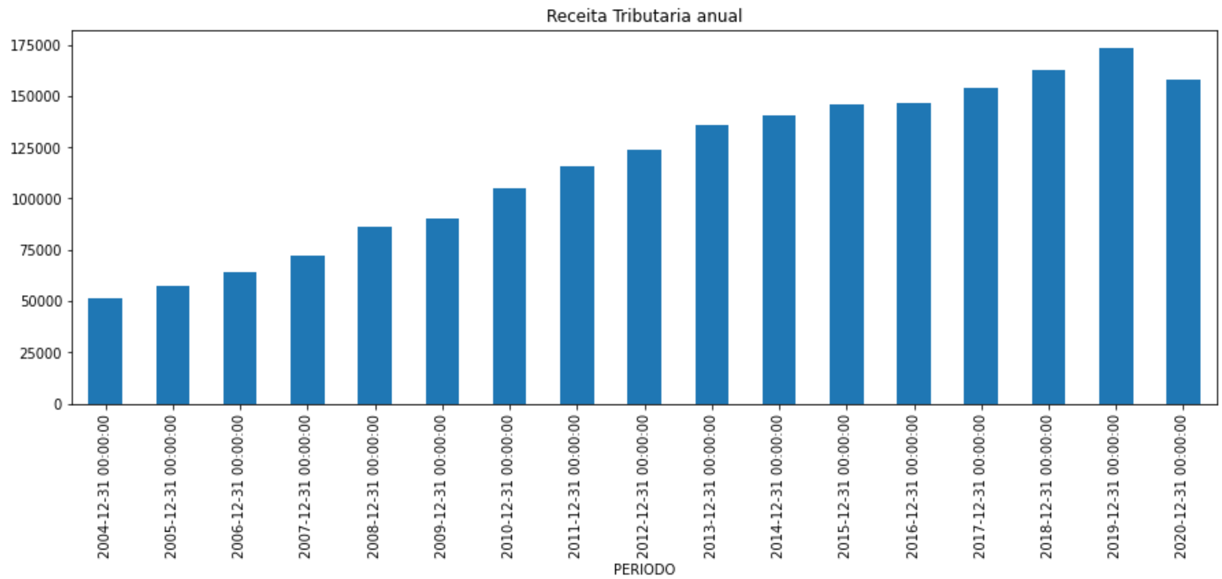


In [21]:
```
title='SP - Receita Tributária ICMS (em milhões R$)'
ylabel='Receita'
xlabel=''

ax = df['ICMS'].plot(figsize=(15,5),title=title);
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



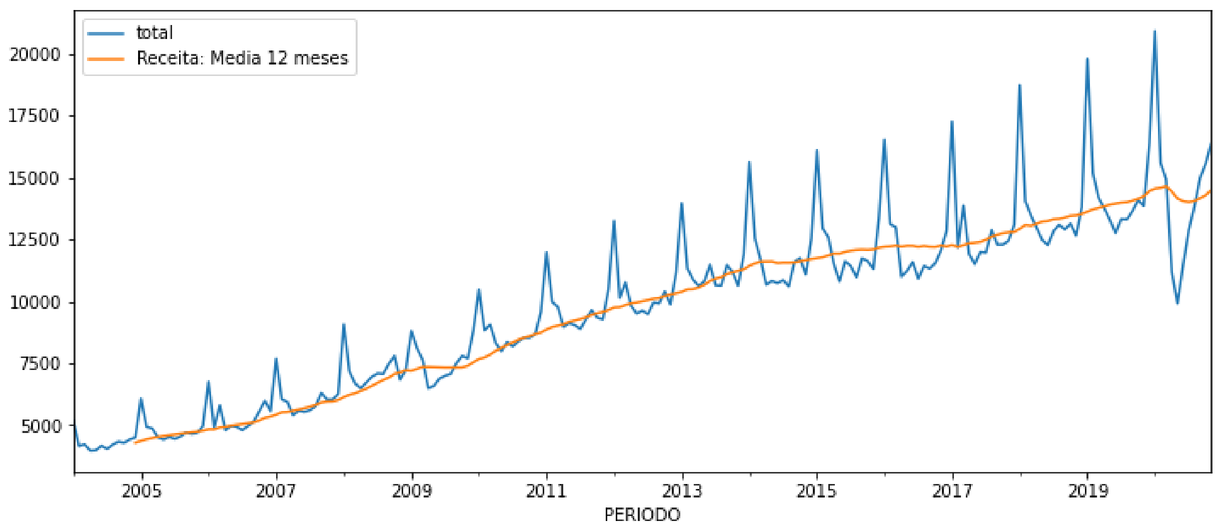
- É possível observar uma tendência nos dois gráficos.
- Possívelmente, pelo fato de que a Arrecadação de São Paulo é fortemente afetada pela arrecadação do ICMS

In [22]:
```
# Variação por ano
df['total'].resample('A').sum().plot.bar(figsize = (15,5),x = df.index, title='Re
```



- **Será inserida uma média de 12 meses, para observar tendência**

In [23]:
```
df['Receita: Media 12 meses'] = df['total'].rolling(window=12).mean()
df[['total','Receita: Media 12 meses']].plot(figsize=(12,5)).autoscale(axis='x',t
```



Utilizando Statsmodels para obter tendência

O [filtro Hodrick-Prescott (https://en.wikipedia.org/wiki/Hodrick%E2%80%93Prescott_filter)](https://en.wikipedia.org/wiki/Hodrick%E2%80%93Prescott_filter) separa uma série temporal y_t em uma componente de tendência τ_t e uma componente cíclica c_t

$$y_t = \tau_t + c_t$$

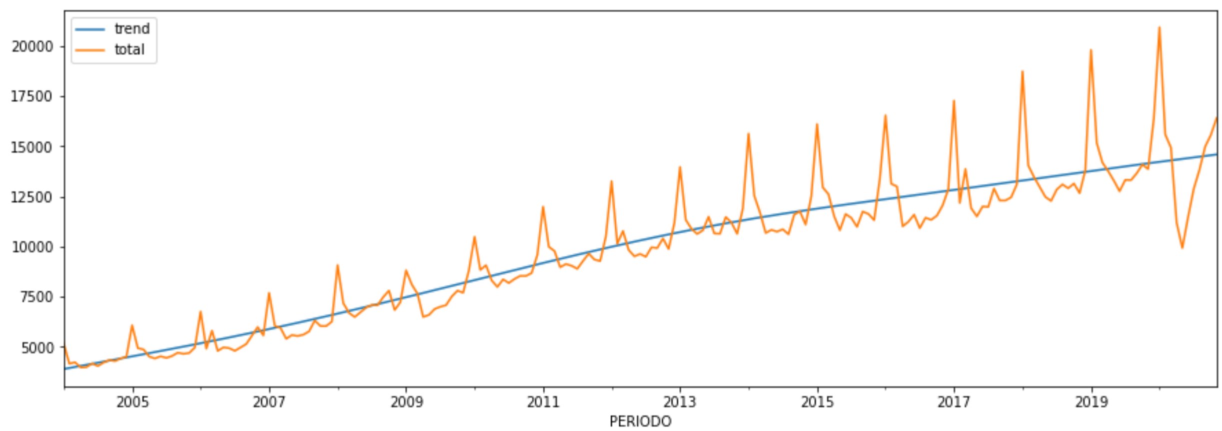
Conforme a fonte:
[https://www.statsmodels.org/stable/generated/statsmodels.tsa.filters.hp_filter.hpfilter.html (https://www.statsmodels.org/stable/generated/statsmodels.tsa.filters.hp_filter.hpfilter.html)](https://www.statsmodels.org/stable/generated/statsmodels.tsa.filters.hp_filter.hpfilter.html)

O valor **lamb** a ser utilizado deve ser **129600** para dados mensais.

In [24]:
```
from statsmodels.tsa.filters.hp_filter import hpfilter

# Separando as variáveis
rec_cycle, rec_trend = hpfilter(df['total'], lamb=129600)
```

In [25]:
```
df['trend'] = rec_trend
```

In [26]:
```
df[['trend','total']].plot(figsize = (15,5)).autoscale(axis='x',tight=True);
```

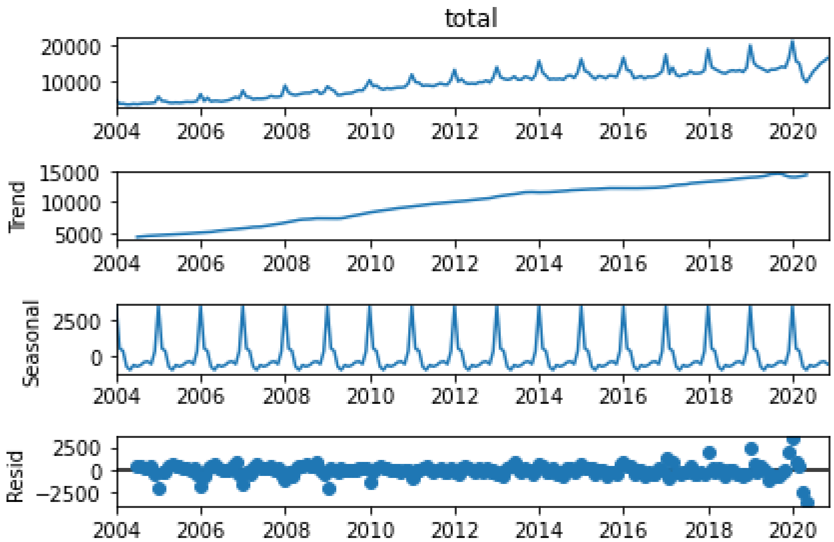


ETS

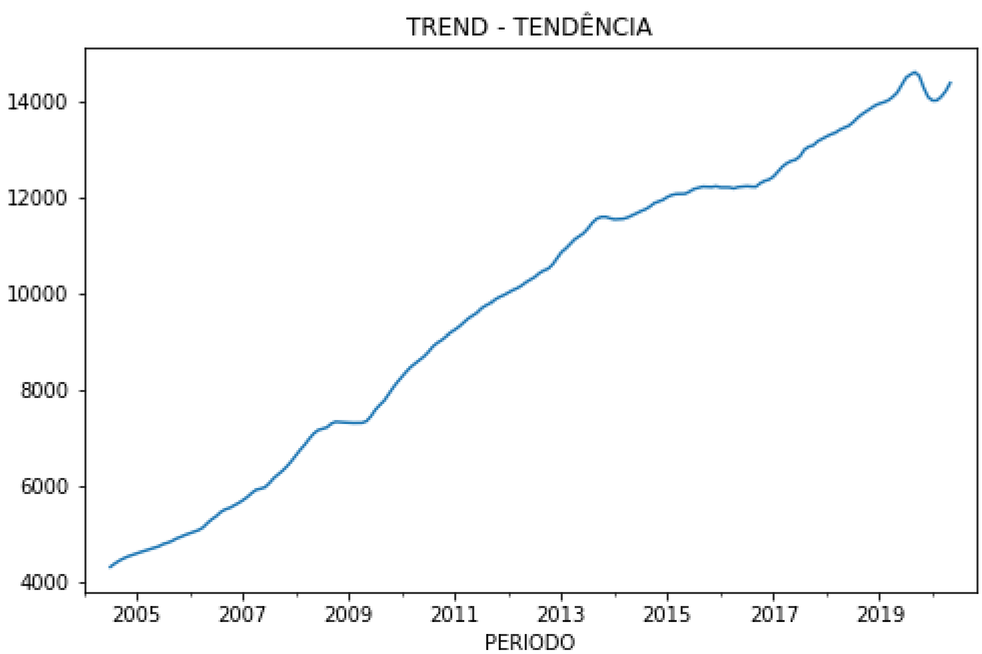
Error / Trend / Seasonality Models

A [decomposição (https://en.wikipedia.org/wiki/Decomposition_of_time_series)](https://en.wikipedia.org/wiki/Decomposition_of_time_series) de uma série temporal tenta isolar componentes insividuais como *erro*, *tendência*, and *sazonalidade* (ETS).

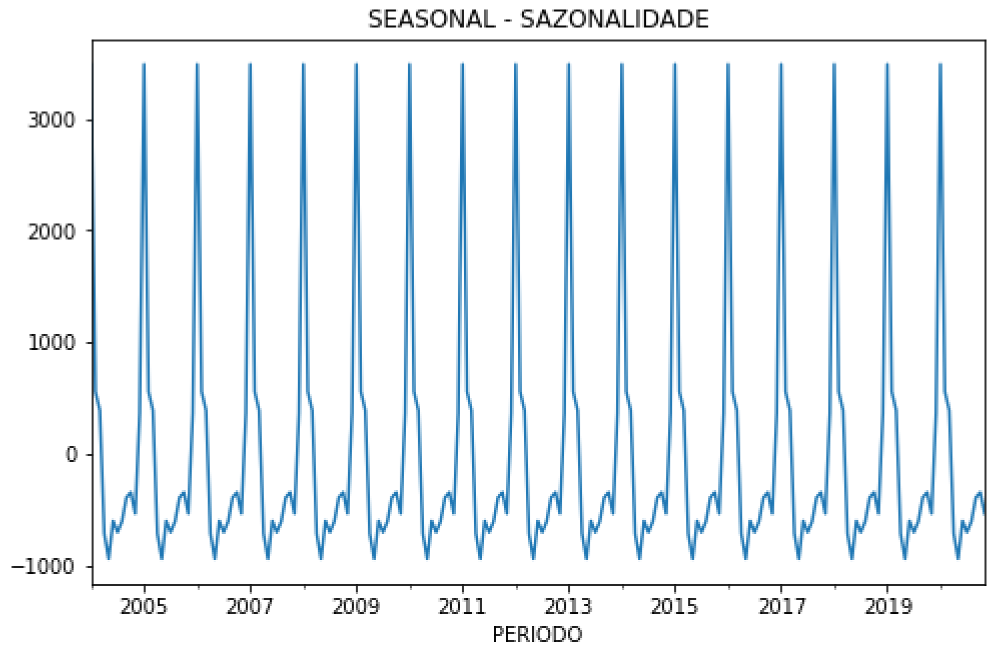
In [27]:
```
from statsmodels.tsa.seasonal import seasonal_decompose

resultado = seasonal_decompose(df['total'], model='add')
resultado.plot();
```



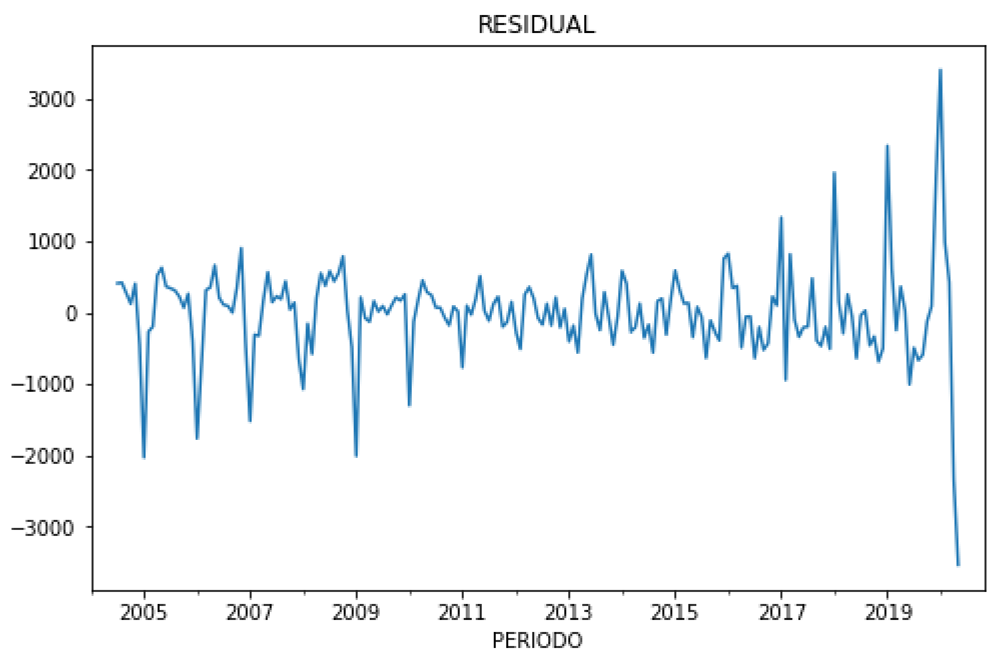
In [28]:
```
resultado.trend.plot(title='TREND - TENDÊNCIA', figsize=(8,5));
```



In [29]:
```
resultado.seasonal.plot(title='SEASONAL - SAZONALIDADE', figsize=(8,5));
```



In [30]:
```
resultado.resid.plot(title='RESIDUAL', figsize=(8,5));
```



Holt-Winters Methods

- *Fonte:* [https://otexts.com/fpp2/holt-winters.html (https://otexts.com/fpp2/holt-winters.html)](https://otexts.com/fpp2/holt-winters.html)
- Método Holt-Winters lida com casos de sazonalidade.
- Possui três equações:
  - uma para ajuste de nível
  - outra para ajuste do crescimento

- outra para sazonalidade

Divisão dos dados

In [31]:
```
train = df.loc[:'2016-12-01']
test = df.loc['2017-01-01':]
```

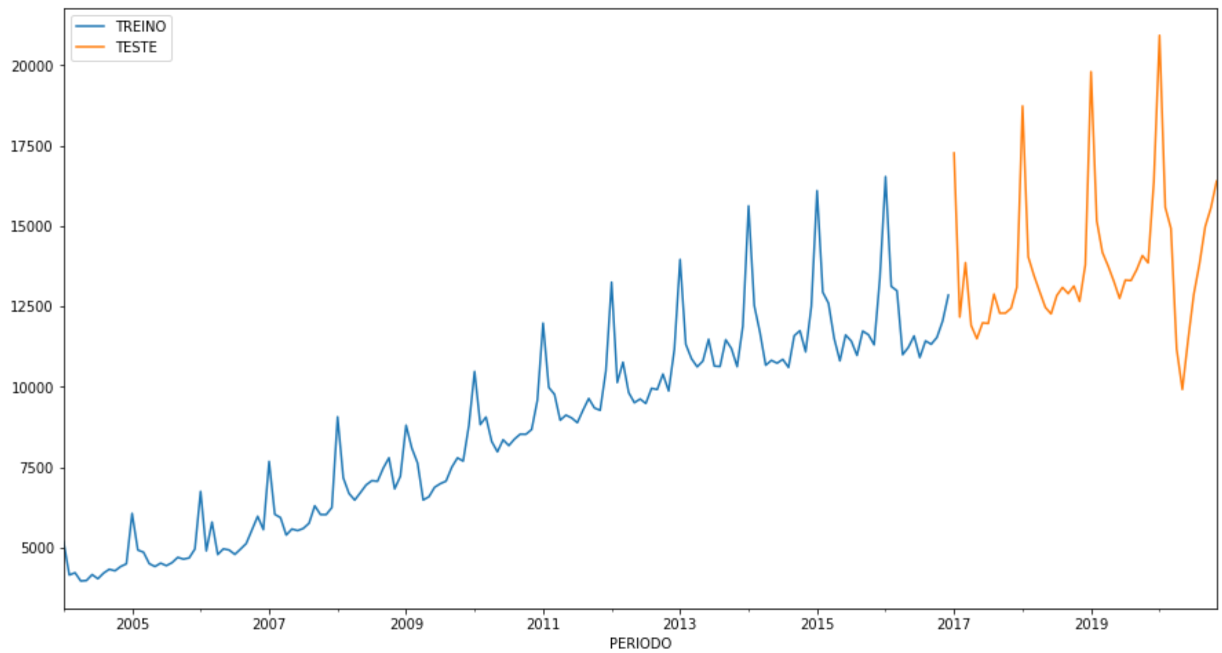
In [32]:
```
from statsmodels.tsa.holtwinters import ExponentialSmoothing

fitted_model = ExponentialSmoothing(train['total'],trend='add',seasonal='add',sea
```

In [33]:
```
test_predictions = fitted_model.forecast(47).rename('Previsão - Holt-Winters - SP
```

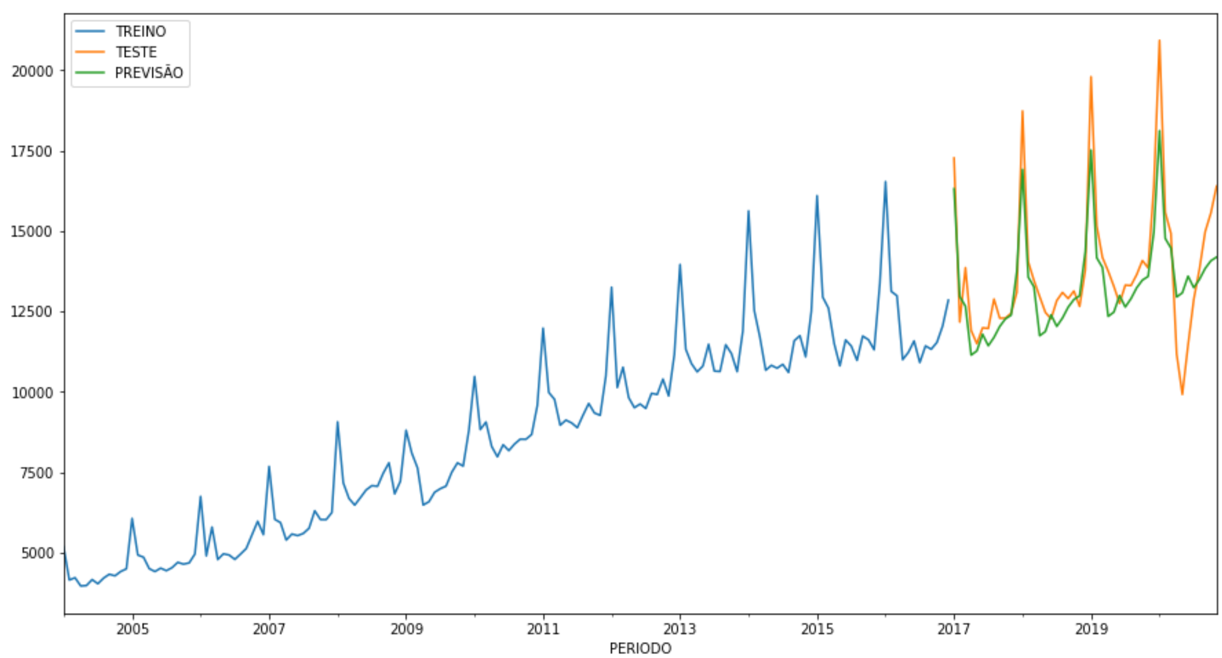
In [34]:
```
test_predictions
```

Out[34]:
```
2017-01-01    16313.258789
2017-02-01    12965.400096
2017-03-01    12664.358017
2017-04-01    11144.574542
2017-05-01    11276.319094
2017-06-01    11792.376250
2017-07-01    11435.035541
2017-08-01    11695.506526
2017-09-01    12033.678837
2017-10-01    12271.472866
2017-11-01    12385.763185
2017-12-01    13758.165560
2018-01-01    16915.030555
2018-02-01    13567.171863
2018-03-01    13266.129783
2018-04-01    11746.346309
2018-05-01    11878.090860
2018-06-01    12394.148016
2018-07-01    12036.807307
2018-08-01    12297.278293
2018-09-01    12635.450604
2018-10-01    12873.244632
2018-11-01    12987.534951
2018-12-01    14359.937326
2019-01-01    17516.802322
2019-02-01    14168.943629
2019-03-01    13867.901550
2019-04-01    12348.118075
2019-05-01    12479.862627
2019-06-01    12995.919782
2019-07-01    12638.579073
2019-08-01    12899.050059
2019-09-01    13237.222370
2019-10-01    13475.016398
2019-11-01    13589.306718
2019-12-01    14961.709092
2020-01-01    18118.574088
2020-02-01    14770.715395
2020-03-01    14469.673316
2020-04-01    12949.889841
2020-05-01    13081.634393
2020-06-01    13597.691549
2020-07-01    13240.350840
2020-08-01    13500.821825
2020-09-01    13838.994136
2020-10-01    14076.788165
2020-11-01    14191.078484
Freq: MS, Name: Previsão - Holt-Winters - SP, dtype: float64
```

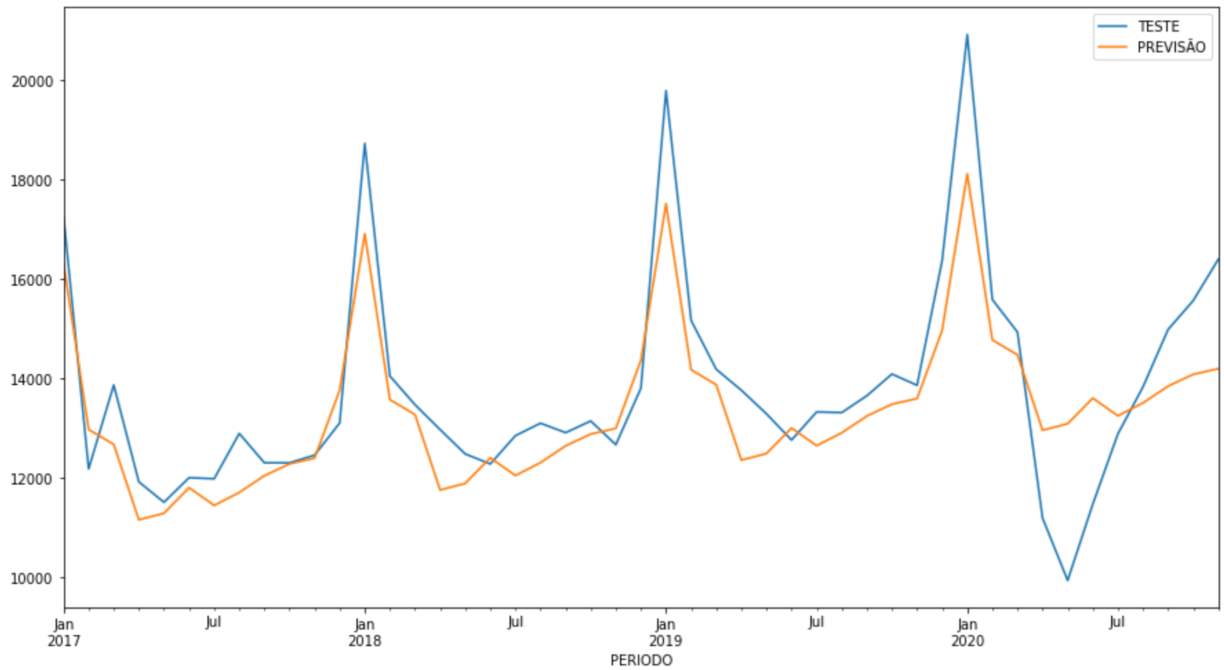
In [35]:
```
train['total'].plot(legend=True,label='TREINO')
test['total'].plot(legend=True,label='TESTE',figsize=(15,8));
```



In [36]:
```
train['total'].plot(legend=True,label='TREINO')
test['total'].plot(legend=True,label='TESTE',figsize=(15,8))
test_predictions.plot(legend=True,label='PREVISÃO');
```



In [37]:
```
test['total'].plot(legend=True,label='TESTE',figsize=(15,8))
test_predictions.plot(legend=True,label='PREVISÃO',xlim=['2017-01-01','2020-11-01
```



In [38]:
```
from sklearn.metrics import mean_squared_error,mean_absolute_error
```

In [39]:
```
mean_absolute_error(test['total'],test_predictions)
```

Out[39]: 868.2068336290454

In [40]:
```
mean_squared_error(test['total'],test_predictions)
```

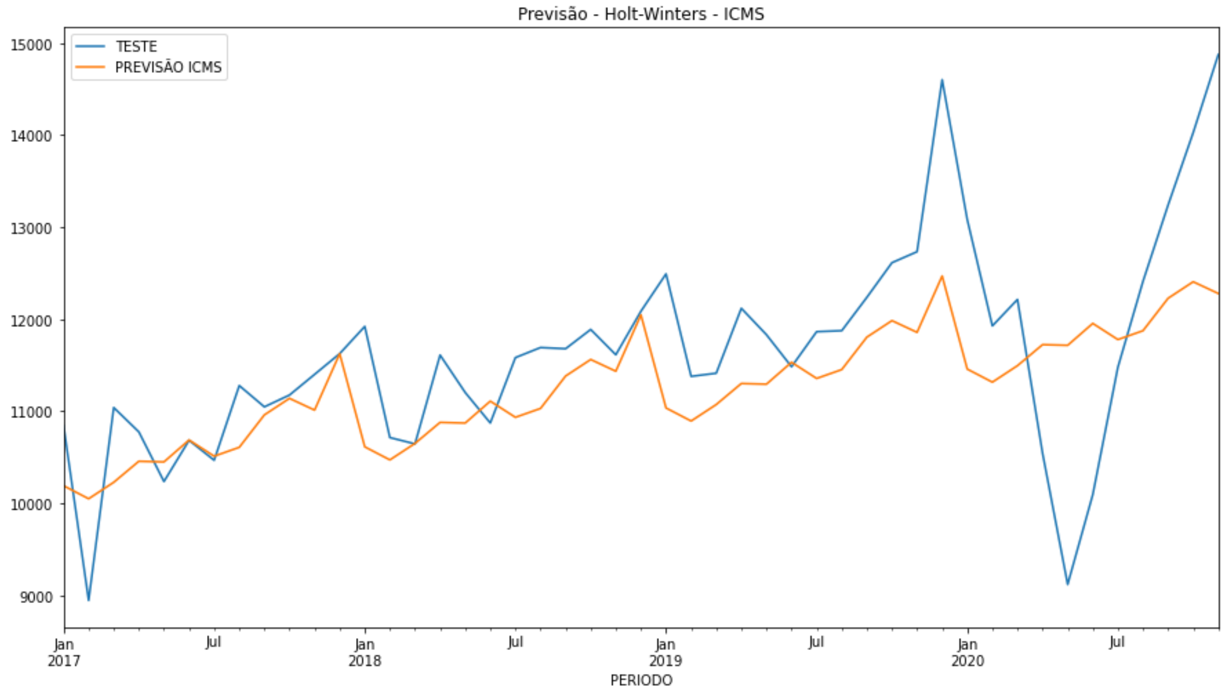
Out[40]: 1284943.0136480625

In [41]:
```
np.sqrt(mean_squared_error(test['total'],test_predictions))
```

Out[41]: 1133.5532689944757

Comparando Dados: ICMS

In [42]:
```
fitted_model_ICMS = ExponentialSmoothing(train['ICMS'],trend='add',seasonal='add'
test_predictions_ICMS = fitted_model_ICMS.forecast(47).rename('Previsão - Holt-Wi
test['ICMS'].plot(legend=True,label='TESTE',figsize=(15,8), title = 'Previsão - H
test_predictions_ICMS.plot(legend=True,label='PREVISÃO ICMS',xlim=['2017-01-01','
```

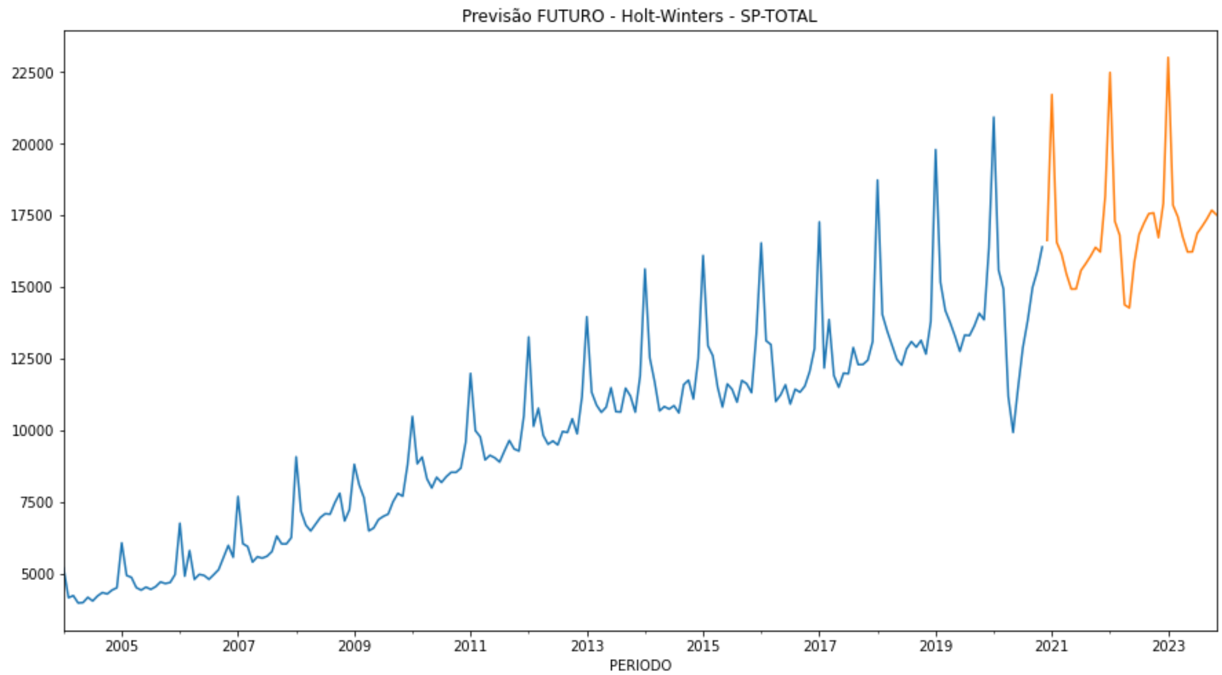


Prevendo Futuro - "Holt-Winters"

In [43]:
```
modelo_HW_final = ExponentialSmoothing(df['total'],trend='add',seasonal='add',sea
```

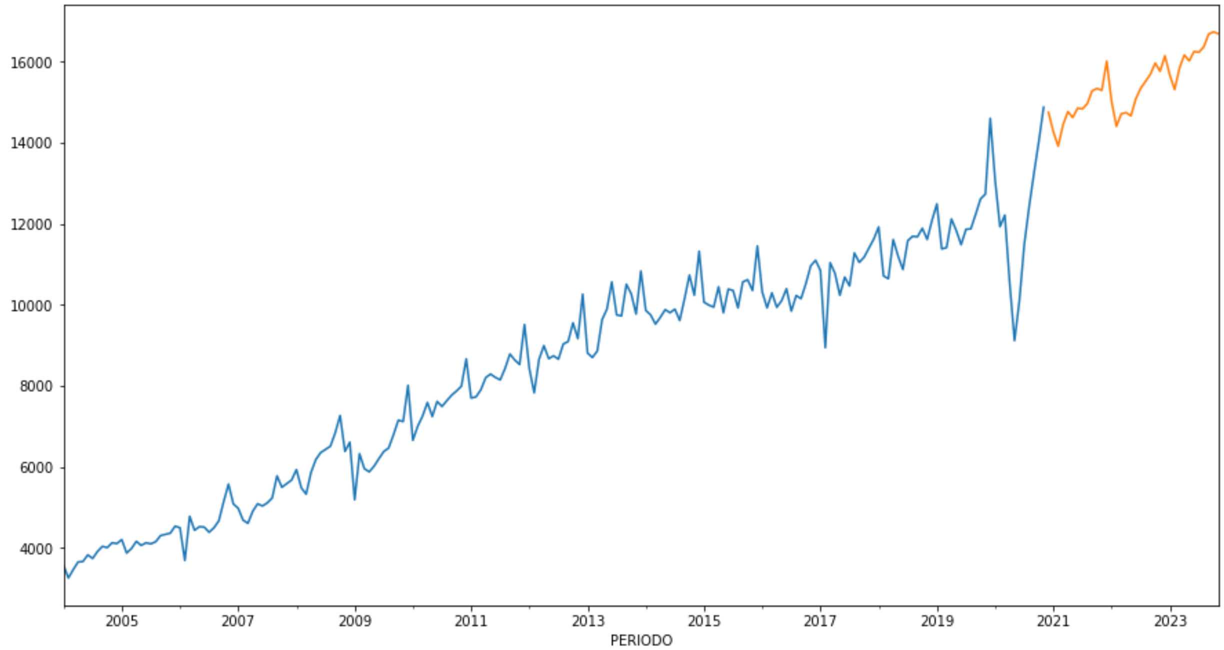
In [44]:
```
predição_HW = modelo_HW_final.forecast(36)
```

```
In [45]: df['total'].plot(figsize=(15,8), title = 'Previsão FUTURO - Holt-Winters - SP-TOT
         predição_HW.plot();
```



Previsão HOLT-WINTERS: ICMS

In [46]:
```
modelo_HW_final_ICMS = ExponentialSmoothing(df['ICMS'],trend='add',seasonal='add'
predição_HW_ICMS = modelo_HW_final_ICMS.forecast(36)
df['ICMS'].plot(figsize=(15,8))
predição_HW_ICMS.plot();
```



SARIMA

Automatizar o teste de Dickey-Fuller Test Aumentado

- Código extraído do curso "Python for Time Series Data Analysis" - Jose Portilla

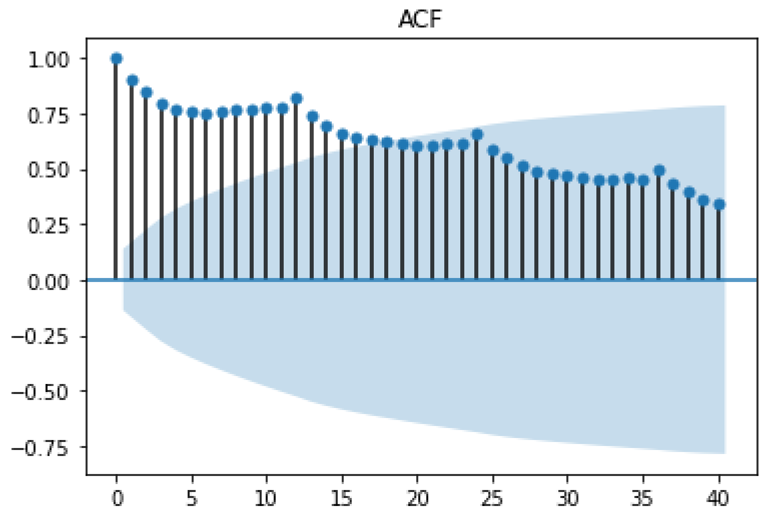
In [47]:
```
from statsmodels.tsa.stattools import adfuller

def adf_test(series,title=''):
    """
    Passar uma série temporal e um titulo opcional, retorna um relatório ADF
    """
    print(f'Teste de Dickey-Fuller Aumentado: {title}')
    result = adfuller(series.dropna(),autolag='AIC') # .dropna() para lidar com d

    labels = ['ADF teste estatístico','p-value','# lags used','# observações']
    out = pd.Series(result[0:4],index=labels)

    for key,val in result[4].items():
        out[f'valor crítico ({key})']=val

    print(out.to_string())          # .to_string() removes the line "dtype: float

    if result[1] <= 0.05:
        print("Fortes evidências contra a hipótese nula")
        print("Rejeita a hipótese nula")
        print("É estacionário")
    else:
        print("Fracas evidências contra a hipótese nula")
        print("Falha ao rejeitar a hipótese nula")
        print("É não-estacionária")
```

In [48]:
```
adf_test(df['total'])
```

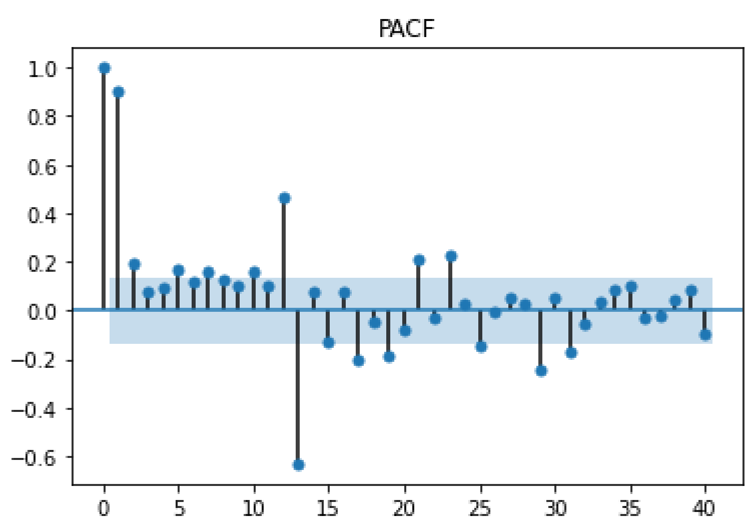
```
Teste de Dickey-Fuller Aumentado:
ADF teste estatístico     -1.083664
p-value                    0.721542
# lags used               15.000000
# observações            187.000000
valor crítico (1%)        -3.465812
valor crítico (5%)        -2.877123
valor crítico (10%)       -2.575077
Fracas evidências contra a hipótese nula
Falha ao rejeitar a hipótese nula
É não-estacionária
```

In [49]:
```
from statsmodels.graphics.tsaplots import plot_acf,plot_pacf
```

In [50]:
```
plot_acf(df['total'],title='ACF',lags=40);
```



In [51]:
```
plot_pacf(df['total'],title='PACF',lags=40);
```



- Neste projeto vamos optar por utilizar o Auto-Arima para partir de um modelo e melhorar se houver necessidade a partir do sugerido automaticamente.

AUTO-ARIMA

Rodar `pmdarima.auto_arima` para obter as ordens recomendadas

In [52]:
```
!pip install pmdarima
```

```
Requirement already satisfied: pmdarima in /usr/local/lib/python3.6/dist-packag
es (1.8.0)
Requirement already satisfied: scipy>=1.3.2 in /usr/local/lib/python3.6/dist-pa
ckages (from pmdarima) (1.4.1)
Requirement already satisfied: Cython<0.29.18,>=0.29 in /usr/local/lib/python3.
6/dist-packages (from pmdarima) (0.29.17)
Requirement already satisfied: scikit-learn>=0.22 in /usr/local/lib/python3.6/d
ist-packages (from pmdarima) (0.22.2.post1)
Requirement already satisfied: pandas>=0.19 in /usr/local/lib/python3.6/dist-pa
ckages (from pmdarima) (1.1.5)
Requirement already satisfied: statsmodels!=0.12.0,>=0.11 in /usr/local/lib/pyt
hon3.6/dist-packages (from pmdarima) (0.12.1)
Requirement already satisfied: numpy>=1.17.3 in /usr/local/lib/python3.6/dist-p
ackages (from pmdarima) (1.19.5)
Requirement already satisfied: setuptools!=50.0.0,>=38.6.0 in /usr/local/lib/py
thon3.6/dist-packages (from pmdarima) (51.3.3)
Requirement already satisfied: urllib3 in /usr/local/lib/python3.6/dist-package
s (from pmdarima) (1.24.3)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.6/dist-pa
ckages (from pmdarima) (1.0.0)
Requirement already satisfied: pytz>=2017.2 in /usr/local/lib/python3.6/dist-pa
ckages (from pandas>=0.19->pmdarima) (2018.9)
Requirement already satisfied: python-dateutil>=2.7.3 in /usr/local/lib/python
3.6/dist-packages (from pandas>=0.19->pmdarima) (2.8.1)
Requirement already satisfied: patsy>=0.5 in /usr/local/lib/python3.6/dist-pack
ages (from statsmodels!=0.12.0,>=0.11->pmdarima) (0.5.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.6/dist-packag
es (from python-dateutil>=2.7.3->pandas>=0.19->pmdarima) (1.15.0)
```

In [53]:
```
# Load specific forecasting tools
from statsmodels.tsa.statespace.sarimax import SARIMAX

from statsmodels.graphics.tsaplots import plot_acf,plot_pacf # for determining (p
from statsmodels.tsa.seasonal import seasonal_decompose      # for ETS Plots
from pmdarima import auto_arima                              # for determining AR
```

```
In [54]: auto_arima(df['total'],seasonal=True,m=12).summary()
```

Out[54]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	203
Model:	SARIMAX(2, 0, 3)x(2, 1, [], 12)	**Log Likelihood**	-1473.355
Date:	Wed, 27 Jan 2021	**AIC**	2964.711
Time:	00:48:24	**BIC**	2993.981
Sample:	0	**HQIC**	2976.567
	- 203		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
intercept	364.8409	134.020	2.722	0.006	102.166	627.515
ar.L1	1.2985	0.238	5.455	0.000	0.832	1.765
ar.L2	-0.6926	0.172	-4.029	0.000	-1.030	-0.356
ma.L1	-0.7895	0.246	-3.209	0.001	-1.272	-0.307
ma.L2	0.3930	0.108	3.630	0.000	0.181	0.605
ma.L3	0.2053	0.121	1.691	0.091	-0.033	0.443
ar.S.L12	-0.2334	0.095	-2.462	0.014	-0.419	-0.048
ar.S.L24	-0.1610	0.093	-1.729	0.084	-0.344	0.022
sigma2	2.871e+05	2.17e+04	13.207	0.000	2.45e+05	3.3e+05

Ljung-Box (L1) (Q):	0.00	**Jarque-Bera (JB):**	256.78
Prob(Q):	0.99	**Prob(JB):**	0.00
Heteroskedasticity (H):	3.48	**Skew:**	-1.19
Prob(H) (two-sided):	0.00	**Kurtosis:**	8.16

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

Ajustar modelo SARIMA(2,0,3)(2,1,0,12)

In [55]:
```
model_sarima = SARIMAX(train['total'],order=(2,0,3),seasonal_order=(2,1,0,12))
results_sarima = model_sarima.fit()
results_sarima.summary()
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/base/model.py:568: Convergen
ceWarning: Maximum Likelihood optimization failed to converge. Check mle_retval
s
  ConvergenceWarning)
```

Out[55]:

SARIMAX Results

Dep. Variable:	total	**No. Observations:**	156
Model:	SARIMAX(2, 0, 3)x(2, 1, [], 12)	**Log Likelihood**	-1067.247
Date:	Wed, 27 Jan 2021	**AIC**	2150.494
Time:	00:48:28	**BIC**	2174.253
Sample:	01-01-2004	**HQIC**	2160.149
	- 12-01-2016		
Covariance Type:	opg		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
ar.L1	1.8389	0.133	13.834	0.000	1.578	2.099
ar.L2	-0.8393	0.132	-6.348	0.000	-1.098	-0.580
ma.L1	-1.4603	0.156	-9.378	0.000	-1.766	-1.155
ma.L2	0.4311	0.164	2.625	0.009	0.109	0.753
ma.L3	0.0372	0.125	0.299	0.765	-0.207	0.281
ar.S.L12	-0.4196	0.099	-4.253	0.000	-0.613	-0.226
ar.S.L24	-0.1254	0.089	-1.410	0.158	-0.300	0.049
sigma2	1.666e+05	5.87e-07	2.84e+11	0.000	1.67e+05	1.67e+05

Ljung-Box (L1) (Q):	0.02	**Jarque-Bera (JB):**	0.34
Prob(Q):	0.89	**Prob(JB):**	0.84
Heteroskedasticity (H):	2.06	**Skew:**	0.02
Prob(H) (two-sided):	0.01	**Kurtosis:**	3.24

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 4.68e+27. Standard errors may be unstable.

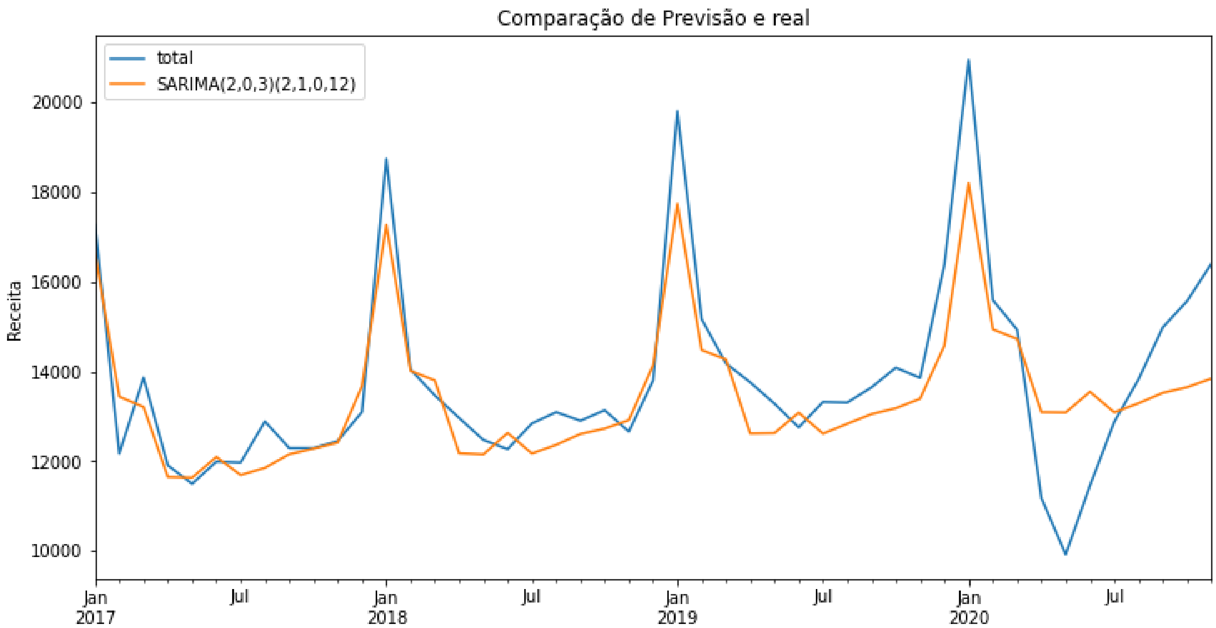
In [56]:

```
# Obtendo a previsão
inicio = len(train)
fim = len(train)+len(test)-1
predictions_sarima = results_sarima.predict(start=inicio, end=fim, dynamic=False,
```

In [57]:
```python
# Comparando a previsão com os valores esperados
for i in range(len(predictions_sarima)):
    print(f"predicted={predictions_sarima[i]:<11.10}, expected={test['total'][i]}
```

```
predicted=16641.67492, expected=17269.8
predicted=13438.11685, expected=12171.3
predicted=13207.73814, expected=13862.3
predicted=11650.56091, expected=11909.5
predicted=11635.21778, expected=11498.5
predicted=12097.83491, expected=11992.5
predicted=11693.58141, expected=11972.4
predicted=11853.01   , expected=12885.7
predicted=12156.84866, expected=12293.5
predicted=12280.96993, expected=12293.3
predicted=12414.3669 , expected=12447.5
predicted=13674.28432, expected=13096.3
predicted=17264.65707, expected=18732.9
predicted=14011.99163, expected=14042.4
predicted=13800.53172, expected=13465.4
predicted=12179.10382, expected=12963.5
predicted=12153.19248, expected=12472.8
predicted=12629.01388, expected=12269.9
predicted=12174.76768, expected=12840.3
predicted=12364.68471, expected=13092.2
predicted=12606.04346, expected=12900.8
predicted=12726.40578, expected=13136.5
predicted=12914.30269, expected=12658.6
predicted=14139.91533, expected=13798.4
predicted=17735.40798, expected=19796.5
predicted=14476.25759, expected=15163.6
predicted=14267.75294, expected=14178.6
predicted=12618.48502, expected=13757.2
predicted=12626.29259, expected=13281.6
predicted=13081.67814, expected=12752.8
predicted=12613.55547, expected=13319.4
predicted=12834.05847, expected=13306.4
predicted=13049.05448, expected=13645.0
predicted=13180.42913, expected=14083.1
predicted=13390.94667, expected=13856.5
predicted=14572.21827, expected=16371.3
predicted=18188.88798, expected=20927.6
predicted=14936.95476, expected=15584.4
predicted=14723.15919, expected=14927.8
predicted=13091.93799, expected=11178.5
predicted=13085.21959, expected=9922.3
predicted=13545.81374, expected=11459.1
predicted=13088.0657 , expected=12875.2
predicted=13290.19004, expected=13823.9
predicted=13522.35817, expected=14981.4
predicted=13647.85676, expected=15562.8
predicted=13840.32092, expected=16395.6
```

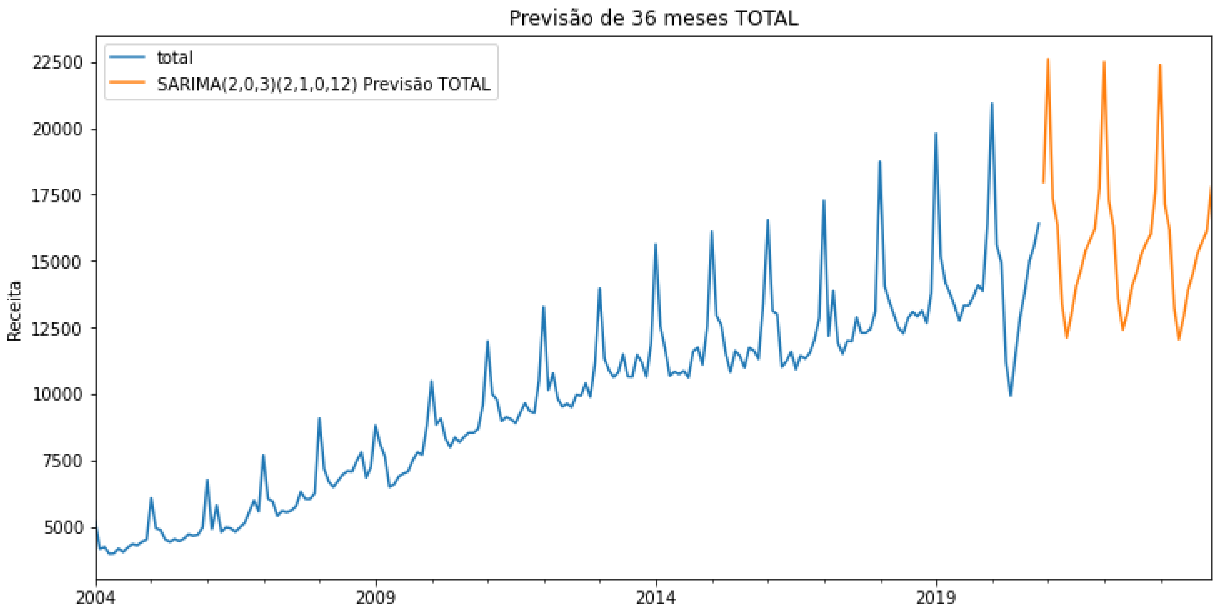
In [58]:
```
# Plotar previsões em relação aos valores conhecidos
title = 'Comparação de Previsão e real'
ylabel='Receita'
xlabel=''

ax = test['total'].plot(legend=True,figsize=(12,6),title=title)
predictions_sarima.plot(legend=True)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



Prevendo o futuro com SARIMA

In [59]:
```
modelo_final_sarima = SARIMAX(df['total'],order=(2,0,3),seasonal_order=(2,1,0,12)
resultado_final_sarima = modelo_final_sarima.fit()
previsao_final_sarima = resultado_final_sarima.predict(len(df),len(df)+36,typ='le
```

In [60]:
```
# Plotar previsões de 36 meses para frente
title = 'Previsão de 36 meses TOTAL'
ylabel='Receita'
xlabel=''

ax = df['total'].plot(legend=True,figsize=(12,6),title=title)
previsao_final_sarima.plot(legend=True)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



Prevendo futuro com SARIMA: ICMS

In [61]:
```
auto_arima(df['ICMS'],seasonal=True,m=12).summary()
```

Out[61]:

SARIMAX Results

Dep. Variable:	y	**No. Observations:**	203
Model:	SARIMAX(1, 1, 1)x(1, 0, 1, 12)	**Log Likelihood**	-1530.217
Date:	Wed, 27 Jan 2021	**AIC**	3072.434
Time:	00:49:21	**BIC**	3092.283
Sample:	0	**HQIC**	3080.465
	- 203		
Covariance Type:	opg		

	coef	std err	z	P>|z|	[0.025	0.975]
intercept	3.8729	2.182	1.775	0.076	-0.403	8.149
ar.L1	0.5838	0.045	13.080	0.000	0.496	0.671
ma.L1	-0.9686	0.020	-49.011	0.000	-1.007	-0.930
ar.S.L12	0.8009	0.106	7.534	0.000	0.593	1.009
ma.S.L12	-0.4326	0.156	-2.773	0.006	-0.738	-0.127
sigma2	2.134e+05	1.34e+04	15.922	0.000	1.87e+05	2.4e+05

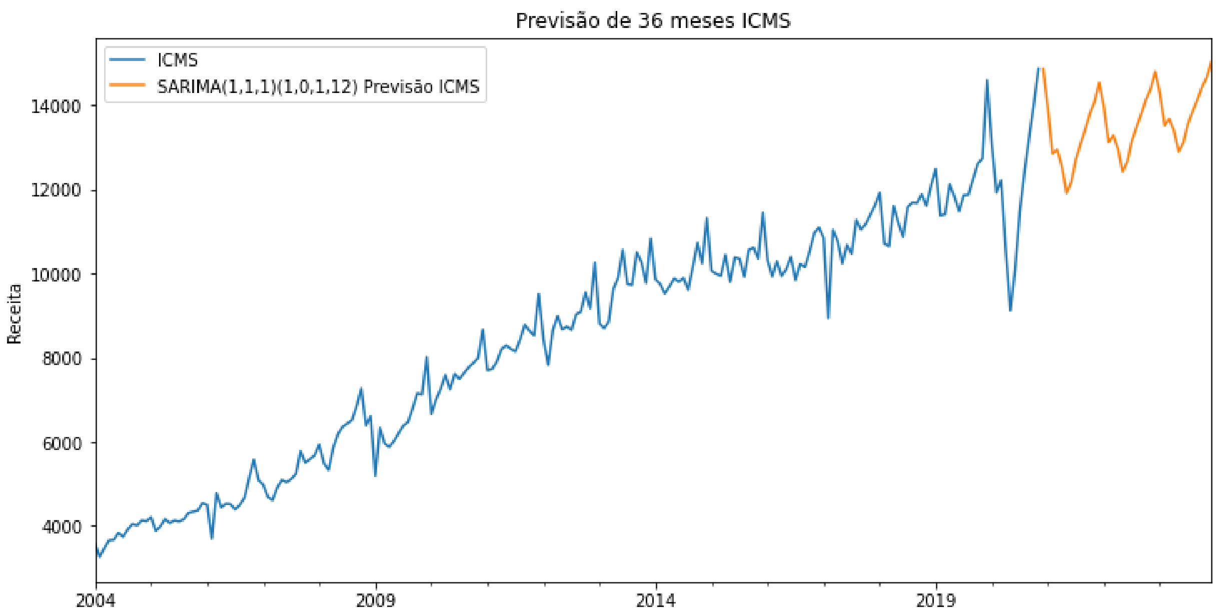
Ljung-Box (L1) (Q):	0.55	**Jarque-Bera (JB):**	207.64
Prob(Q):	0.46	**Prob(JB):**	0.00
Heteroskedasticity (H):	3.70	**Skew:**	-0.72
Prob(H) (two-sided):	0.00	**Kurtosis:**	7.75

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

Prevendo futuro com SARIMA: ICMS

In [62]:

```
modelo_final_sarima_ICMS = SARIMAX(df['ICMS'],order=(1,1,1),seasonal_order=(1,0,1
resultado_final_sarima_ICMS = modelo_final_sarima_ICMS.fit()
previsao_final_sarima_ICMS = resultado_final_sarima_ICMS.predict(len(df),len(df)+

# Plotar previsões de 36 meses para frente
title = 'Previsão de 36 meses ICMS'
ylabel='Receita'
xlabel=''

ax = df['ICMS'].plot(legend=True,figsize=(12,6),title=title)
previsao_final_sarima_ICMS.plot(legend=True)
ax.autoscale(axis='x',tight=True)
ax.set(xlabel=xlabel, ylabel=ylabel);
```



In [62]: