Original Image

Table 1. Parameters for Policy Process in Regime-Switching Model

	μ_1	μ_2	ρ_1	ρ_2	σ_1	σ_2
Extreme Assumptions	.0005	.0007	.80	.932	.0015	.0015
Calibration To U.S. Data	.0013	.003	.75	.60	.0019	.0024

Calibration to U.S. data achieved by splitting sample into two "regimes" 1959:2-1971:12/1983:4-2000:07 and 1972:1-1982:12 (excluding 1983:1-1983:3 due to exceptionally high money growth rates) and fitting AR (1) processes to the monthly growth rate of M2 in each period.

Table 2. Impacts of Policy Interventions at 48-Month Horizon

	Direct Effects $\eta^*_{P,T+K}$ (Standard Deviations)		Expectations-Formation Effects (Standard Deviations)	
Specification	p	y	p	y
	Extreme Case			
A	4.53	3.45	0.86	-3.50
B	5.34	0.22	0.04	-0.17
C	2.07	1.61	0.16	-0.63
D	4.53	3.45	0.30	-1.20
E	1.30	1.04	0.48	-2.01
	Less Extreme Case			
A	4.54	3.32	0.02	-0.06
B	5.55	0.19	0.01	-0.05
E	1.30	1.04	0.03	-0.10

Direct Effects (η^*) and Expectations-Formation Effects scaled by standard errors of direct effects based on 5000 draws.
Interventions:
A: $\tilde{\varepsilon}_P = .667$ in each of 48 months
B: $\tilde{\varepsilon}_P = 8.0$ for first 4 months, $\tilde{\varepsilon} = 0$ for next 44 months
C: $\tilde{\varepsilon}_P = 0.333$ in each of 48 months
D: $\tilde{\varepsilon}_P = .6667$ in each of 48 months, but $p_{22} = 0.9167$ (1-year duration of Regime 2)
In Specifications A-D, $P(R_T = R^1) = .98$.
E: $\tilde{\varepsilon}_P = 0.2$ in each of 48 months, but $P(R_T = R^1) = .02$.

In [21]:
```
import tensorflow as tf
import matplotlib.pyplot as plt

from tensorflow.keras import Sequential
from tensorflow.keras.models import Model
from tensorflow.keras.layers import BatchNormalization
from tensorflow.keras.layers import Conv2D
from tensorflow.keras.layers import MaxPooling2D
from tensorflow.keras.layers import Activation
from tensorflow.keras.layers import Dropout
from tensorflow.keras.layers import Lambda
from tensorflow.keras.layers import Dense
from tensorflow.keras.layers import Flatten
from tensorflow.keras.layers import Input, Concatenate, UpSampling2D

import datetime

from PIL import Image
import statistics
import pytesseract
```

In [22]:
```
image_height=1024
image_width=1024
```

In [23]:
```
def normalize(input_image):
    input_image = tf.cast(input_image, tf.float32) / 255.0
    #input_mask -= 1
    return input_image
```

In [24]:
```
def decode_image(image):
    img=tf.io.decode_jpeg(image)
    img=tf.image.resize(img, [image_height, image_width])
    return img
```

In [25]:
```
def decode_mask(image):
    img=tf.io.decode_jpeg(image,channels=1)
    img=tf.image.resize(img, [image_height, image_width])
    return img
```

In [26]:
```
def process_1(file_paths):
    img = normalize(decode_image(tf.io.read_file(file_paths)))
    return img
```

In [27]:
```
def process_2(file_paths):
    img = normalize(decode_image(tf.io.read_file(file_paths)))

    mask_path=tf.strings.regex_replace(file_paths,'.jpg','.jpeg')

    tab_mask=tf.strings.regex_replace(mask_path,"Image_Data", "Table_Data")
    col_mask=tf.strings.regex_replace(mask_path,"Image_Data", "Column_Data")

    table_mask = normalize(decode_mask(tf.io.read_file(tab_mask)))
    column_mask=normalize(decode_mask(tf.io.read_file(col_mask)))

    return img, {'table_mask':table_mask,'column_mask':column_mask}
```

In [28]:
```
def create_mask(pred_mask1, pred_mask2):
    pred_mask1 = tf.argmax(pred_mask1, axis=-1)
    pred_mask1 = pred_mask1[..., tf.newaxis]

    pred_mask2 = tf.argmax(pred_mask2, axis=-1)
    pred_mask2 = pred_mask2[..., tf.newaxis]
    return pred_mask1[0], pred_mask2[0]
```

In [29]:
```
def show_prediction_sample_image(dataset=None, num=1):

    model = tf.keras.models.load_model('../input/model50/all/mymodel_45')

    for image in dataset.take(num):
        pred_mask1, pred_mask2 = model.predict(image, verbose=1)
        table_mask, column_mask = create_mask(pred_mask1, pred_mask2)

        im=tf.keras.preprocessing.image.array_to_img(image[0])
        im.save('image.bmp')

        im=tf.keras.preprocessing.image.array_to_img(table_mask)
        im.save('table_mask.bmp')

        im=tf.keras.preprocessing.image.array_to_img(column_mask)
        im.save('column_mask.bmp')

        return True
```

In [30]:
```
def generate_segment():
    img_org  = Image.open('./image.bmp')
    img_mask = Image.open('./table_mask.bmp')

    img_mask = img_mask.convert('L')
    img_org.putalpha(img_mask)
    img_org.save('output.png')
```

In [31]:
```
def ocr_core(filename):
    text = pytesseract.image_to_string(Image.open(filename))  # We'll use Pill
ow's Image class to open the image and pytesseract to detect the string in the
image
    return text
```

In [32]:
```
def get_mask(dataset=None, num=1):

    table=[]
    column=[]
    for i in dataset:
        table.append(i[1]['table_mask'])
        column.append(i[1]['column_mask'])

    model = tf.keras.models.load_model('../input/model50/all/mymodel_45')

    pred_tab=[]
    pred_col=[]
    for image, (mask1, mask2) in dataset.take(num):
        pred_mask1, pred_mask2 = model.predict(image, verbose=1)
        table_mask, column_mask = create_mask(pred_mask1, pred_mask2)
        pred_tab.append(table_mask)
        pred_col.append(column_mask)

    return table,column,pred_tab,pred_col
```

In [33]:
```
def get_accuracy(orig_table,orig_column,pred_table,pred_column):
    mask_1=[]
    mask_2=[]
    for i in pred_table:
        t2=tf.reshape(i, [1,1024, 1024])
        mask_1.append(t2)

    for i in pred_column:
        t2=tf.reshape(i, [1,1024, 1024])
        mask_2.append(t2)

    m = tf.keras.metrics.Accuracy()
    m.update_state(orig_table,mask_1)
    table_accuracy=m.result().numpy()

    m=tf.keras.metrics.Accuracy()
    m.update_state(orig_column,mask_2)
    column_accuracy=m.result().numpy()

    mean_accuracy=(table_accuracy + column_accuracy)/2

    return mean_accuracy
```

In [ ]:

In [34]:
```python
def final_1(path):
    list_ds = tf.data.Dataset.list_files(path)
    DATASET_SIZE = len(list(list_ds))
    test_size = DATASET_SIZE
    test = list_ds.take(test_size)
    BATCH_SIZE = 1
    BUFFER_SIZE = 1000
    test = test.map(process_1)
    test_dataset = test.batch(BATCH_SIZE)

    flag=show_prediction_sample_image(test_dataset)
    generate_segment()
    text=ocr_core('output.png')

    return text
```

In [35]:
```python
def final_2(path1):
    list_ds = tf.data.Dataset.list_files(path1)
    DATASET_SIZE = len(list(list_ds))
    test_size = DATASET_SIZE
    test = list_ds.take(test_size)
    BATCH_SIZE = 1
    BUFFER_SIZE = 1000
    test = test.map(process_2)
    test_dataset = test.batch(BATCH_SIZE)

    #flag=show_prediction_sample_image(test_dataset)
    #generate_segment()

    orig_table,orig_column,pred_table,pred_column=get_mask(test_dataset)

    accuracy=get_accuracy(orig_table,orig_column,pred_table,pred_column)

    return accuracy
```

In [41]:
```
img_path='../input/Data/Image_Data/*'
table_mask='../input/Data/Table_Data/*'
col_mask='../input/Data/Column_Data/*'

start_time = datetime.datetime.now()

text_output=final_1(img_path)
print(text_output)

end_time=datetime.datetime.now()

print("------------------------------------------------------------------------------")
print("Total time taken with GPU:",(end_time-start_time))
print("------------------------------------------------------------------------------")
```

```
. wh oe A Pe: a a
Extreme .0005 0007 80 932 0015 0015
Assumptions
Calibration
ToU.S. Data 0013 75 60 0019 -0024
Calibration to U.S poh =a sgimes” 1959:2-
1971:12/1983:4 2960: 7 an 1-.983:3 due to
exceptionally «gh mon i seas > monthly
growth rate of M2 in each deriod.
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Tew fieets tions-
2 tormation Effects
(Stai_as ssations) (Standard Doviations)
Specification P y P y
Extreme Case
A 4.53 3.45 0.86 -3.50
B 5.34 0.22 0.04 -0.17
GS 2.07 1.61 0.16 -0.63
D 453 3.45 0.30 =1.20
E 1.30 1.04 048 -2.01
LessE.. me Case
A 454 3.32 0.02 =0.06
B 3.55 0.19 0.01 -0.05
E 1.30 1.04 0.03 =0.10
Direct Eff~ oe =
direct eff
Inter
```

```
2b
```

```
---------------------------------------------------------------------------
Total time taken with GPU: 0:00:06.594485
---------------------------------------------------------------------------
```

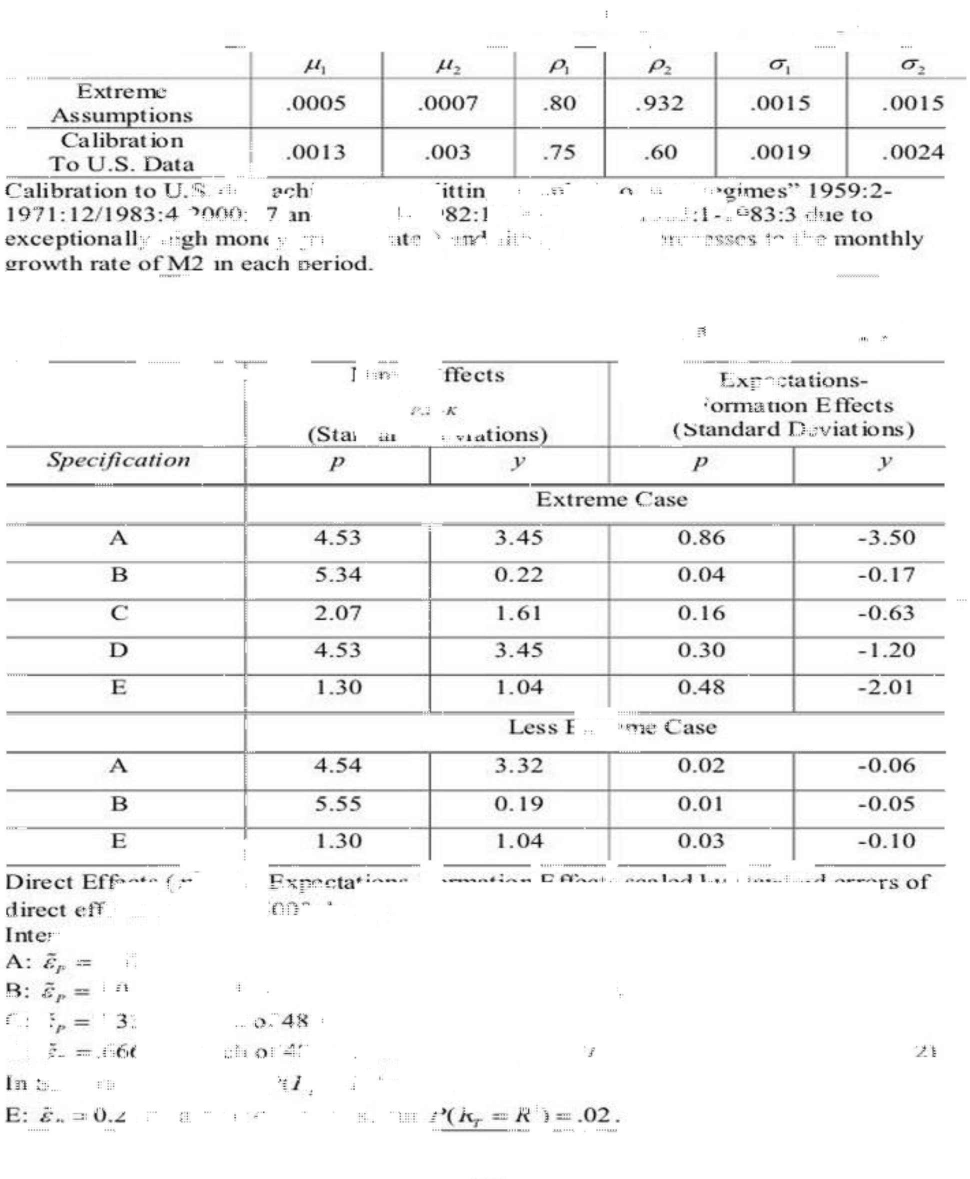
In [ ]:

In [ ]:

In [1]:
```
acc=final_2(img_path)
print("Accuracy:",acc)
```

Accuracy: 0.8476290702819824

Image segment



	μ_1	μ_2	ρ_1	ρ_2	σ_1	σ_2
Extreme Assumptions	.0005	.0007	.80	.932	.0015	.0015
Calibration To U.S. Data	.0013	.003	.75	.60	.0019	.0024

Calibration to U.S. [illegible] achi[illegible] ittin[illegible] gimes" 1959:2-1971:12/1983:4 2000: 7 an[illegible] '82:1 [illegible] :1-[illegible]83:3 due to exceptionally [illegible]igh mon[illegible] [illegible] and [illegible] [illegible]sses to the monthly growth rate of M2 in each period.

Specification	[illegible] ffects (Sta[illegible] [illegible]iations) p	y	Expectations-[illegible]ormation Effects (Standard Deviations) p	y
	Extreme Case			
A	4.53	3.45	0.86	-3.50
B	5.34	0.22	0.04	-0.17
C	2.07	1.61	0.16	-0.63
D	4.53	3.45	0.30	-1.20
E	1.30	1.04	0.48	-2.01
	Less E[illegible]me Case			
A	4.54	3.32	0.02	-0.06
B	5.55	0.19	0.01	-0.05
E	1.30	1.04	0.03	-0.10

Direct Eff[illegible] Expectatio[illegible] [illegible]rs of direct eff[illegible]

Inter[illegible]

A: $\tilde{\varepsilon}_p =$ [illegible]

B: $\tilde{\varepsilon}_p =$ [illegible]

C: $\tilde{\varepsilon}_p =$ 3[illegible] [illegible].48 [illegible]

[illegible]

In [illegible]

E: $\tilde{\varepsilon}_p = 0.2$ [illegible] $P(k_T = R) = .02$.

28

In [ ]: