Assignment 3 - Logistic Regression

In [1]:
```
# This code appears in every demonstration Notebook.
# By default, when you run each cell, only the last output of the codes will show.
# This code makes all outputs of a cell show.
from IPython.core.interactiveshell import InteractiveShell
InteractiveShell.ast_node_interactivity = "all"
```

In this assignment, we will build logistic regression models to detect accounting fraud using financial statement features.
The data was collected by Bao et al. (2020) based on the detected material accounting misstatements disclosed in the SEC's Accounting and Auditing Enforcement Releases (AAERs).
The dataset covers all publicly listed U.S. firms over the period 1990– 2014. The variable name of the fraud label is "misstate" (1 denotes fraud, and 0 denotes non-fraud).
We will use both raw financial data from the financial statements and the financial ratios that are used to evaluate the financial performance of a company for detection.

You may find the description of variables in the Word document.

1. Import the libraries

In [2]:
```
import pandas as pd
import statsmodels.api as sm
import math
import matplotlib.pyplot as plt
import numpy as np
```

1. Read in the dataset and display basic information about the dataset.

In [3]:
```
fraud = pd.read_csv('AccountingFraud.csv')
```

In [4]:
```
fraud.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 146045 entries, 0 to 146044
Data columns (total 44 columns):
 #   Column       Non-Null Count   Dtype  
---  ------       --------------   -----  
 0   fyear        146045 non-null  int64  
 1   misstate     146045 non-null  int64  
 2   act          146045 non-null  float64
 3   ap           146045 non-null  float64
 4   at           146045 non-null  float64
 5   ceq          146045 non-null  float64
 6   che          146045 non-null  float64
 7   cogs         146045 non-null  float64
 8   csho         146045 non-null  float64
 9   dlc          146045 non-null  float64
 10  dltis        146045 non-null  float64
 11  dltt         146045 non-null  float64
 12  dp           146045 non-null  float64
 13  ib           146045 non-null  float64
 14  invt         146045 non-null  float64
 15  ivao         146045 non-null  float64
 16  ivst         146045 non-null  float64
 17  lct          146045 non-null  float64
 18  lt           146045 non-null  float64
 19  ni           146045 non-null  float64
 20  ppegt        146045 non-null  float64
 21  pstk         146045 non-null  float64
 22  re           146045 non-null  float64
 23  rect         146045 non-null  float64
 24  sale         146045 non-null  float64
 25  sstk         146045 non-null  float64
 26  txp          146045 non-null  float64
 27  txt          146045 non-null  float64
 28  xint         146045 non-null  float64
 29  prcc_f       146045 non-null  float64
 30  dch_wc       141286 non-null  float64
 31  ch_rsst      141194 non-null  float64
 32  dch_rec      141302 non-null  float64
 33  dch_inv      141430 non-null  float64
 34  soft_assets  145453 non-null  float64
 35  ch_cs        130127 non-null  float64
 36  ch_cm        128938 non-null  float64
 37  ch_roa       133367 non-null  float64
 38  issue        146045 non-null  int64  
 39  bm           146027 non-null  float64
 40  dpi          136817 non-null  float64
 41  reoa         145454 non-null  float64
 42  EBIT         145454 non-null  float64
 43  ch_fcf       140638 non-null  float64
dtypes: float64(41), int64(3)
memory usage: 49.0 MB
```

In [5]:
```
fraud.columns
```

Out[5]:
```
Index(['fyear', 'misstate', 'act', 'ap', 'at', 'ceq', 'che', 'cogs', 'csho',
       'dlc', 'dltis', 'dltt', 'dp', 'ib', 'invt', 'ivao', 'ivst', 'lct', 'lt',
       'ni', 'ppegt', 'pstk', 're', 'rect', 'sale', 'sstk', 'txp', 'txt',
       'xint', 'prcc_f', 'dch_wc', 'ch_rsst', 'dch_rec', 'dch_inv',
       'soft_assets', 'ch_cs', 'ch_cm', 'ch_roa', 'issue', 'bm', 'dpi', 'reoa',
       'EBIT', 'ch_fcf'],
      dtype='object')
```

In [6]:
```
fraud.head()
```

Out[6]:

	fyear	misstate	act	ap	at	ceq	che	cogs	csho	dlc	...	soft_assets	ch_cs	ch_cm	ch_roa	issue	
0	1990	0	10.047	3.736	32.335	6.262	0.002	30.633	2.526	3.283	...	0.312448	0.095082	0.082631	-0.019761	1	0.4
1	1990	0	1.247	0.803	7.784	0.667	0.171	1.125	3.556	0.021	...	0.315904	0.188832	-0.211389	-0.117832	1	0.1
2	1990	0	55.040	3.601	118.120	44.393	3.132	107.343	3.882	6.446	...	0.605342	0.097551	-0.105780	0.091206	1	2.2
3	1990	0	24.684	3.948	34.591	7.751	0.411	31.214	4.755	8.791	...	0.793068	-0.005725	-0.249704	0.017545	1	1.0
4	1990	0	17.325	3.520	27.542	-12.142	1.017	32.662	6.735	32.206	...	0.869182	-0.231536	-1.674893	-0.466667	0	-1.6

5 rows × 44 columns

1. Explore the variable 'misstate' with a graph. What do you observe?

In [7]:
```
misstate_counts = fraud['misstate'].value_counts()
misstate_counts
```

Out[7]:
```
misstate
0    145081
1       964
Name: count, dtype: int64
```

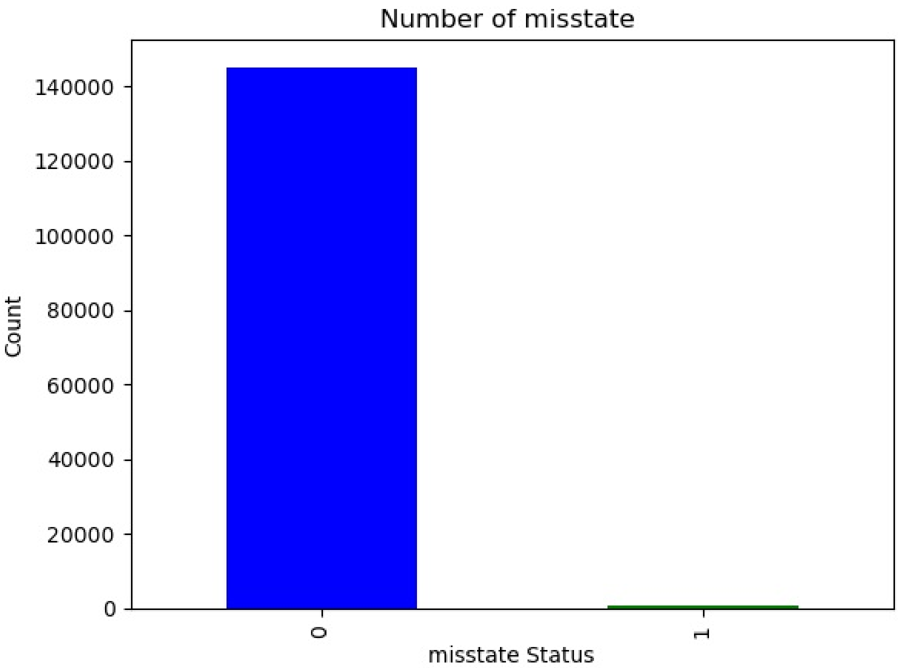
In [8]:
```
misstate_counts.plot(kind='bar', color=['blue', 'green'])

# Add title and labels
plt.title('Number of misstate ')
plt.xlabel('misstate Status')
plt.ylabel('Count')
plt.show()
```

Out[8]:
```
<Axes: xlabel='misstate'>
```

Out[8]:
```
Text(0.5, 1.0, 'Number of misstate ')
```

Out[8]:
```
Text(0.5, 0, 'misstate Status')
```

Out[8]:
```
Text(0, 0.5, 'Count')
```



the count of misstate(0) is very high 145081 but misstate(1) is low 964

1. Next we sum the number of fraud cases by year and make a line graph.
   First we need to use .groupby() method to do the sum. We did not go over this in class. I explain here. Then you can use the result to create a line graph.

In [ ]:
```

```

In [9]:
```
fraud_by_year=fraud.groupby('fyear')['misstate'].sum().reset_index()
fraud_by_year

# Groupby method group the data observations by the given variable 'fyear'
# into groups.
# Then the sum() will sum the variable 'misstate'
# reset_index() is to transform the result into a dataframe
```

Out[9]:

	fyear	misstate
0	1990	15
1	1991	27
2	1992	26
3	1993	30
4	1994	23
5	1995	22
6	1996	33
7	1997	42
8	1998	56
9	1999	73
10	2000	86
11	2001	81
12	2002	77
13	2003	69
14	2004	58
15	2005	45
16	2006	33
17	2007	30
18	2008	26
19	2009	31
20	2010	26
21	2011	21
22	2012	19
23	2013	11
24	2014	4

In [ ]:

Save the output of the code above and make a line graph based on it. What do you observe?

In [10]:

```
# Create a line graph
plt.plot(fraud_by_year['fyear'], fraud_by_year['misstate'])

# Add title and labels
plt.title('Number of misstate by Year')
plt.xlabel('Year')
plt.ylabel('Number of misstate')

# Show the graph
plt.show()
```

Out[10]:

```
[<matplotlib.lines.Line2D at 0x1458b0ed0>]
```

Out[10]:

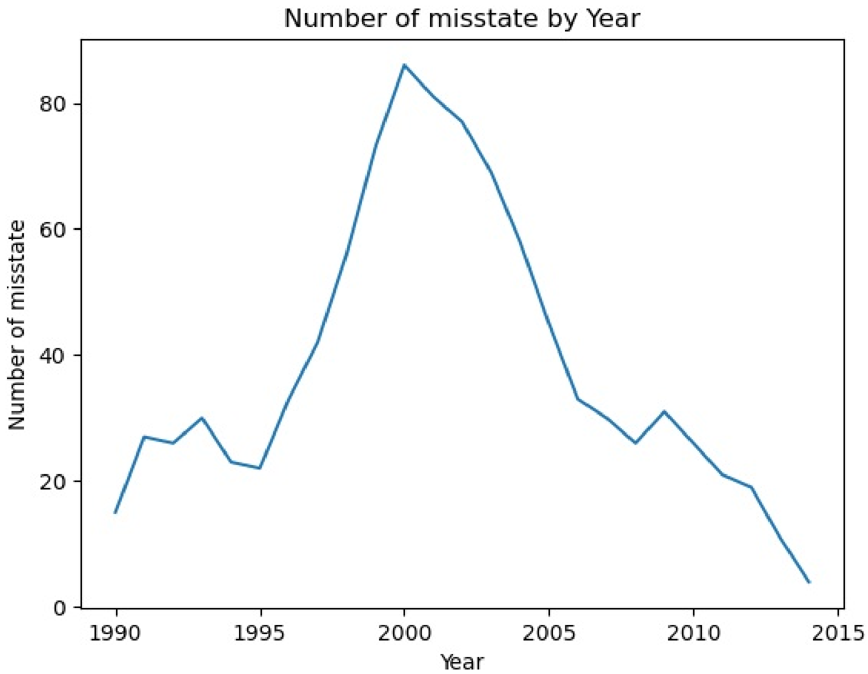
```
Text(0.5, 1.0, 'Number of misstate by Year')
```

Out[10]:

```
Text(0.5, 0, 'Year')
```

Out[10]:

```
Text(0, 0.5, 'Number of misstate')
```



The graph shows a significant increase in the number of misstates from 1995, peaking around 2000 before gradually declining. By 2005 to 2010, it returns to a level similar to that of 1995.

1. Missing values. You may notice that some variables have missing values.
   Ideally, we need to handle missing values carefully. We will explore that in the future if we have the chance.
   For now, we just simply drop the observations with missing values.

In [11]:
```
fraud = fraud.dropna()
fraud
```

Out[11]:

	fyear	misstate	act	ap	at	ceq	che	cogs	csho	dlc	...	soft_assets	ch_cs	ch_cm	
0	1990	0	10.047	3.736	32.335	6.262	0.002	30.633	2.526	3.283	...	0.312448	0.095082	0.082631	-0.
1	1990	0	1.247	0.803	7.784	0.667	0.171	1.125	3.556	0.021	...	0.315904	0.188832	-0.211389	-0.
2	1990	0	55.040	3.601	118.120	44.393	3.132	107.343	3.882	6.446	...	0.605342	0.097551	-0.105780	0.
3	1990	0	24.684	3.948	34.591	7.751	0.411	31.214	4.755	8.791	...	0.793068	-0.005725	-0.249704	0.
4	1990	0	17.325	3.520	27.542	-12.142	1.017	32.662	6.735	32.206	...	0.869182	-0.231536	-1.674893	-0.
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
146039	2014	0	167.320	4.021	1260.060	972.016	159.564	0.000	3896.103	0.000	...	0.015362	-1.718931	0.435251	0.
146040	2014	0	262.600	12.400	1234.800	194.100	166.200	214.400	97.748	23.200	...	0.751944	0.560406	0.127217	-0.
146041	2014	0	1578.400	106.700	4557.600	2459.600	997.300	324.400	182.067	15.100	...	0.742781	-0.118178	0.031360	0.
146042	2014	0	973.800	249.500	2015.900	-4.800	290.500	1185.500	95.831	49.600	...	0.751129	0.004207	-0.037925	0.
146044	2014	0	233.211	5.224	1099.101	873.214	204.821	43.338	58.057	15.678	...	0.068841	1.684618	-0.094348	0.

126483 rows × 44 columns

1. Now let's fit logistic regression models. First, we only use the 28 raw accounting variables as the independent variables. You may find the definitions of them in the Word document.

Prepare the data.

In [12]:
```
import patsy

y_28, X_28 = patsy.dmatrices('misstate ~ act+ap+ at+ ceq+ che+ cogs+ +csho+dlc+ dltis+dltt+ dp+ ib+ invt+ ivao+
                      data = fraud,
                      return_type = 'dataframe')
y_28.head()
X_28.head()
```

Out[12]:

	misstate
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

Out[12]:

	Intercept	act	ap	at	ceq	che	cogs	csho	dlc	dltis	...	ppegt	pstk	re	rect	sale	sstk	txp
0	1.0	10.047	3.736	32.335	6.262	0.002	30.633	2.526	3.283	32.853	...	31.767	0.000	5.420	6.895	40.522	0.000	0.000
1	1.0	1.247	0.803	7.784	0.667	0.171	1.125	3.556	0.021	2.017	...	7.328	0.000	-3.339	0.290	3.635	0.006	0.000
2	1.0	55.040	3.601	118.120	44.393	3.132	107.343	3.882	6.446	6.500	...	78.331	0.000	46.630	47.366	144.258	0.000	0.000
3	1.0	24.684	3.948	34.591	7.751	0.411	31.214	4.755	8.791	0.587	...	11.145	1.295	3.280	8.522	48.292	0.000	0.448
4	1.0	17.325	3.520	27.542	-12.142	1.017	32.662	6.735	32.206	0.000	...	5.782	0.000	-25.955	6.354	33.543	0.000	0.000

5 rows × 29 columns

In [13]:
```
y_28.columns
X_28.columns
```

Out[13]:
```
Index(['misstate'], dtype='object')
```

Out[13]:
```
Index(['Intercept', 'act', 'ap', 'at', 'ceq', 'che', 'cogs', 'csho', 'dlc',
       'dltis', 'dltt', 'dp', 'ib', 'invt', 'ivao', 'ivst', 'lct', 'lt', 'ni',
       'ppegt', 'pstk', 're', 'rect', 'sale', 'sstk', 'txp', 'txt', 'xint',
       'prcc_f'],
      dtype='object')
```

1. Fit the model

In [14]:
```
logit_model_28 = sm.Logit(y_28['misstate'], X_28[['Intercept', 'act', 'ap', 'at', 'ceq', 'che', 'cogs', 'csho',
       'dltis', 'dltt', 'dp', 'ib', 'invt', 'ivao', 'ivst', 'lct', 'lt', 'ni',
       'ppegt', 'pstk', 're', 'rect', 'sale', 'sstk', 'txp', 'txt', 'xint',
       'prcc_f']])
logit_res_28 =  logit_model_28.fit()
logit_res_28.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.041878
         Iterations 9
```

Out[14]:

Logit Regression Results

Dep. Variable:	misstate	**No. Observations:**	126483
Model:	Logit	**Df Residuals:**	126454
Method:	MLE	**Df Model:**	28
Date:	Fri, 01 Mar 2024	**Pseudo R-squ.:**	0.01767
Time:	13:36:57	**Log-Likelihood:**	-5296.8
converged:	True	**LL-Null:**	-5392.1
Covariance Type:	nonrobust	**LLR p-value:**	4.086e-26

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-5.0167	0.035	-141.978	0.000	-5.086	-4.947
act	0.0002	6.49e-05	3.360	0.001	9.09e-05	0.000
ap	0.0003	6.64e-05	4.490	0.000	0.000	0.000
at	-6.578e-07	7.19e-05	-0.009	0.993	-0.000	0.000
ceq	2.411e-05	7.29e-05	0.331	0.741	-0.000	0.000
che	-0.0002	7.26e-05	-2.896	0.004	-0.000	-6.8e-05
cogs	-2.82e-05	2.14e-05	-1.319	0.187	-7.01e-05	1.37e-05
csho	4.195e-05	2.3e-05	1.822	0.068	-3.16e-06	8.71e-05
dlc	-7.837e-05	7.22e-05	-1.086	0.277	-0.000	6.3e-05
dltis	1.371e-05	2.37e-05	0.579	0.562	-3.27e-05	6.01e-05
dltt	4.041e-05	4.01e-05	1.008	0.313	-3.82e-05	0.000
dp	-0.0002	0.000	-1.537	0.124	-0.000	5.33e-05
ib	-9.332e-05	0.000	-0.786	0.432	-0.000	0.000
invt	-9.922e-05	6.94e-05	-1.430	0.153	-0.000	3.67e-05
ivao	-1.974e-06	1.71e-05	-0.115	0.908	-3.55e-05	3.16e-05
ivst	-5.899e-05	7.59e-05	-0.777	0.437	-0.000	8.98e-05
lct	-0.0001	7.03e-05	-1.570	0.116	-0.000	2.74e-05
lt	-4.393e-05	7.89e-05	-0.557	0.578	-0.000	0.000
ni	-1.766e-05	0.000	-0.174	0.862	-0.000	0.000
ppegt	-2.009e-05	7.51e-06	-2.676	0.007	-3.48e-05	-5.38e-06
pstk	-0.0001	0.000	-0.389	0.697	-0.001	0.000
re	-7.699e-06	7.47e-06	-1.030	0.303	-2.23e-05	6.95e-06
rect	-8.394e-05	6.44e-05	-1.303	0.192	-0.000	4.23e-05
sale	1.844e-05	2e-05	0.922	0.357	-2.08e-05	5.77e-05
sstk	0.0002	4.94e-05	4.230	0.000	0.000	0.000
txp	3.215e-05	0.000	0.150	0.881	-0.000	0.000
txt	-1.766e-05	0.000	-0.145	0.885	-0.000	0.000
xint	0.0012	0.000	5.096	0.000	0.001	0.002
prcc_f	0.0009	0.000	4.246	0.000	0.001	0.001

Significant Variables (p < 0.05): act, ap, che, cogs, dlc, invt, sstk, rect, xint, prcc_f

Not Significant Variables (p >= 0.05): at, ceq, csho, dltis, dltt, dp, ib, ivao, ivst, lct, lt, ni, ppegt, pstk, re, txt, txp

1. Make the predictions for probabilities and classify.

In [15]:

```
predicted_28 = logit_res_28.predict(X_28)
predicted_28
```

Out[15]:

```
0         0.006640
1         0.006598
2         0.006643
3         0.006615
4         0.006595
            ...
146039    0.008112
146040    0.007419
146041    0.010544
146042    0.007738
146044    0.006930
Length: 126483, dtype: float64
```

In [16]:

```
predicted_classes_28 = (predicted_28 >= 0.5).astype(int)
```

```
predicted_classes_28[:97613]
```

Out[16]:

```
0         0
1         0
2         0
3         0
4         0
         ..
111354    0
111355    0
111356    0
111357    0
111358    0
Length: 97613, dtype: int64
```

1. Calculate the accuracy rate.

In [17]:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

accuracy_28 = accuracy_score(y_28['misstate'], predicted_classes_28)
conf_matrix_28 = confusion_matrix(y_28['misstate'], predicted_classes_28)
classification_report_str_28 = classification_report(y_28['misstate'], predicted_classes_28)
```

In [18]:

```
print(accuracy_28)
print(conf_matrix_28)
print(classification_report_str_28)
```

```
0.9927974510408514
[[125568      6]
 [   905      4]]
              precision    recall  f1-score   support

         0.0       0.99      1.00      1.00    125574
         1.0       0.40      0.00      0.01       909

    accuracy                           0.99    126483
   macro avg       0.70      0.50      0.50    126483
weighted avg       0.99      0.99      0.99    126483
```

In [ ]:

The model achieved a high accuracy of approximately 99.15%. It correctly predicted 84,983 instances as negative (TN), but incorrectly classified 728 instances as negative when they were positive (FN). There were no instances correctly predicted as positive (TP) or incorrectly predicted as positive (FP). Precision and recall were high for the majority class (class 0), but the model performed poorly for the minority class (class 1), with zero precision, recall, and F1-score

1. Repeat 6-9 using the 14 financial ratio variables.

In [19]:

```
import patsy
y_14, X_14 = patsy.dmatrices('misstate ~ dch_wc + ch_rsst + dch_rec + dch_inv + soft_assets +dpi+ '
           'ch_cs + ch_cm + ch_roa+ch_fcf+reoa+EBIT + issue+bm',
                      data = fraud,
                      return_type = 'dataframe')
y_14.head()
X_14.head()
```

Out[19]:

	misstate
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

Out[19]:

	Intercept	dch_wc	ch_rsst	dch_rec	dch_inv	soft_assets	dpi	ch_cs	ch_cm	ch_roa	ch_fcf	reoa	EBIT
0	1.0	0.069595	0.046043	0.041935	0.033034	0.312448	0.873555	0.095082	0.082631	-0.019761	-0.042140	0.167620	0.161961
1	1.0	-0.065604	-0.240937	-0.006248	-0.026684	0.315904	0.745139	0.188832	-0.211389	-0.117832	0.100228	-0.428957	-0.157888
2	1.0	0.092822	0.020143	0.002156	0.002746	0.605342	1.015131	0.097551	-0.105780	0.091206	0.066348	0.394768	0.063681
3	1.0	0.014060	0.035120	0.035583	0.008332	0.793068	1.026261	-0.005725	-0.249704	0.017545	-0.017358	0.094822	0.088347
4	1.0	-0.540503	-0.575325	-0.102153	-0.222022	0.869182	0.598443	-0.231536	-1.674893	-0.466667	0.130349	-0.942379	-0.700821

In [20]:

```
y_14.columns
X_14.columns
```

Out[20]: Index(['misstate'], dtype='object')

Out[20]:
```
Index(['Intercept', 'dch_wc', 'ch_rsst', 'dch_rec', 'dch_inv', 'soft_assets',
       'dpi', 'ch_cs', 'ch_cm', 'ch_roa', 'ch_fcf', 'reoa', 'EBIT', 'issue',
       'bm'],
      dtype='object')
```

In [21]:
```
logit_model_14 = sm.Logit(y_14['misstate'], X_14[['Intercept', 'dch_wc', 'ch_rsst', 'dch_rec', 'dch_inv', 'soft_
       'dpi', 'ch_cs', 'ch_cm', 'ch_roa', 'ch_fcf', 'reoa', 'EBIT', 'issue',
       'bm']])
logit_res_14 =  logit_model_14.fit()
logit_res_14.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.040796
         Iterations 12
```

Out[21]:

Logit Regression Results

Dep. Variable:	misstate	**No. Observations:**	126483
Model:	Logit	**Df Residuals:**	126468
Method:	MLE	**Df Model:**	14
Date:	Fri, 01 Mar 2024	**Pseudo R-squ.:**	0.04303
Time:	13:36:58	**Log-Likelihood:**	-5160.1
converged:	True	**LL-Null:**	-5392.1
Covariance Type:	nonrobust	**LLR p-value:**	3.716e-90

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-7.1554	0.222	-32.176	0.000	-7.591	-6.720
dch_wc	-0.9463	0.366	-2.586	0.010	-1.663	-0.229
ch_rsst	0.9744	0.283	3.446	0.001	0.420	1.529
dch_rec	2.0044	0.464	4.318	0.000	1.095	2.914
dch_inv	1.2629	0.640	1.973	0.048	0.009	2.517
soft_assets	1.8892	0.149	12.680	0.000	1.597	2.181
dpi	0.0457	0.077	0.591	0.555	-0.106	0.197
ch_cs	0.0576	0.026	2.215	0.027	0.007	0.108
ch_cm	-0.0024	0.015	-0.163	0.870	-0.031	0.026
ch_roa	-0.5019	0.218	-2.307	0.021	-0.928	-0.075
ch_fcf	0.4192	0.237	1.768	0.077	-0.046	0.884
reoa	0.2432	0.040	6.075	0.000	0.165	0.322
EBIT	-0.4304	0.138	-3.125	0.002	-0.700	-0.160
issue	1.2184	0.184	6.630	0.000	0.858	1.579
bm	-0.0688	0.033	-2.083	0.037	-0.134	-0.004

Significant Variables (p < 0.05): ch_rsst, dch_rec, soft_assets, reoa, EBIT, issue

Not Significant Variables (p >= 0.05): dch_wc, dch_inv, dpi, ch_cs, ch_cm, ch_roa, ch_fcf, bm

In [22]:
```
predicted_14 = logit_res_14.predict(X_14)
predicted_14
```

Out[22]:
```
0         0.005159
1         0.004236
2         0.007358
3         0.012228
4         0.003841
            ...
146039    0.001856
146040    0.012347
146041    0.013226
146042    0.010997
146044    0.003742
Length: 126483, dtype: float64
```

In [23]:
```
predicted_classes_14 = (predicted_14 >= 0.5).astype(int)
predicted_classes_14[:97613]
```

Out[23]:
```
0         0
1         0
2         0
3         0
4         0
         ..
111354    0
111355    0
111356    0
111357    0
111358    0
Length: 97613, dtype: int64
```

In [24]:
```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Assuming y_14 and predicted_classes_14 are defined elsewhere
accuracy_14 = accuracy_score(y_14['misstate'], predicted_classes_14)
conf_matrix_14 = confusion_matrix(y_14['misstate'], predicted_classes_14)

classification_report_str_14 = classification_report(y_14['misstate'], predicted_classes_14, zero_division=1)


# Optionally, print or use these metrics as needed
print("Accuracy:", accuracy_14)
print("Confusion Matrix:", conf_matrix_14)
print("Classification Report:", classification_report_str_14)
```

```
Accuracy: 0.992813263442518
Confusion Matrix: [[125574      0]
 [   909      0]]
Classification Report:               precision    recall  f1-score   support

         0.0       0.99      1.00      1.00    125574
         1.0       1.00      0.00      0.00       909

    accuracy                           0.99    126483
   macro avg       1.00      0.50      0.50    126483
weighted avg       0.99      0.99      0.99    126483
```

In [ ]:

The model achieved 99.15% accuracy, mostly identifying negative cases correctly but struggling with positive ones. It didn't predict any positive cases accurately, indicating an imbalance issue that needs addressing.

1. Repeat 6-9 using all 42 (28+14) variables. Which model gives the best accuracy rate?

In [25]:
```
import patsy
y_fraud, X_fraud = patsy.dmatrices('misstate ~ act+ap+ at+ ceq+ che+ cogs+ +csho+dlc+ dltis+dltt+ dp+ ib+ invt+
           'ch_cs + ch_cm + ch_roa+ch_fcf+reoa+EBIT + issue+bm',
                      data = fraud,
                      return_type = 'dataframe')
y_fraud.head()
X_fraud.head()
```

Out[25]:

	misstate
0	0.0
1	0.0
2	0.0
3	0.0
4	0.0

Out[25]:

	Intercept	act	ap	at	ceq	che	cogs	csho	dlc	dltis	...	soft_assets	dpi	ch_cs	ch_cm	ch_roa
0	1.0	10.047	3.736	32.335	6.262	0.002	30.633	2.526	3.283	32.853	...	0.312448	0.873555	0.095082	0.082631	-0.019761
1	1.0	1.247	0.803	7.784	0.667	0.171	1.125	3.556	0.021	2.017	...	0.315904	0.745139	0.188832	-0.211389	-0.117832
2	1.0	55.040	3.601	118.120	44.393	3.132	107.343	3.882	6.446	6.500	...	0.605342	1.015131	0.097551	-0.105780	0.091206
3	1.0	24.684	3.948	34.591	7.751	0.411	31.214	4.755	8.791	0.587	...	0.793068	1.026261	-0.005725	-0.249704	0.017545
4	1.0	17.325	3.520	27.542	-12.142	1.017	32.662	6.735	32.206	0.000	...	0.869182	0.598443	-0.231536	-1.674893	-0.466667

5 rows × 43 columns

In [26]:
```
y_fraud.columns
X_fraud.columns
```

Out[26]:
```
Index(['misstate'], dtype='object')
```

Out[26]:
```
Index(['Intercept', 'act', 'ap', 'at', 'ceq', 'che', 'cogs', 'csho', 'dlc',
       'dltis', 'dltt', 'dp', 'ib', 'invt', 'ivao', 'ivst', 'lct', 'lt', 'ni',
       'ppegt', 'pstk', 're', 'rect', 'sale', 'sstk', 'txp', 'txt', 'xint',
       'prcc_f', 'dch_wc', 'ch_rsst', 'dch_rec', 'dch_inv', 'soft_assets',
       'dpi', 'ch_cs', 'ch_cm', 'ch_roa', 'ch_fcf', 'reoa', 'EBIT', 'issue',
       'bm'],
      dtype='object')
```

In [27]:
```
logit_model_fraud = sm.Logit(y_fraud['misstate'], X_fraud[['Intercept', 'act', 'ap', 'at', 'ceq', 'che', 'cogs'
       'dltis', 'dltt', 'dp', 'ib', 'invt', 'ivao', 'ivst', 'lct', 'lt', 'ni',
       'ppegt', 'pstk', 're', 'rect', 'sale', 'sstk', 'txp', 'txt', 'xint',
       'prcc_f', 'dch_wc', 'ch_rsst', 'dch_rec', 'dch_inv', 'soft_assets',
       'dpi', 'ch_cs', 'ch_cm', 'ch_roa', 'ch_fcf', 'reoa', 'EBIT', 'issue',
       'bm']])
logit_res_fraud =  logit_model_fraud.fit()
logit_res_fraud.summary()
```

```
Optimization terminated successfully.
         Current function value: 0.040220
         Iterations 12
```

Out[27]:

Logit Regression Results

Dep. Variable:	misstate	**No. Observations:**	126483
Model:	Logit	**Df Residuals:**	126440
Method:	MLE	**Df Model:**	42
Date:	Fri, 01 Mar 2024	**Pseudo R-squ.:**	0.05656
Time:	13:37:00	**Log-Likelihood:**	-5087.2
converged:	True	**LL-Null:**	-5392.1
Covariance Type:	nonrobust	**LLR p-value:**	7.739e-102

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-7.1695	0.225	-31.796	0.000	-7.611	-6.728
act	0.0002	6.59e-05	3.130	0.002	7.71e-05	0.000
ap	0.0003	6.95e-05	4.337	0.000	0.000	0.000
at	-4.644e-06	6.77e-05	-0.069	0.945	-0.000	0.000
ceq	1.881e-05	6.82e-05	0.276	0.783	-0.000	0.000
che	-0.0002	7.46e-05	-2.125	0.034	-0.000	-1.23e-05
cogs	-2.204e-05	2.16e-05	-1.022	0.307	-6.43e-05	2.02e-05
csho	4.306e-05	2.22e-05	1.935	0.053	-5.45e-07	8.67e-05
dlc	-4.019e-05	7.39e-05	-0.544	0.586	-0.000	0.000
dltis	1.254e-06	2.57e-05	0.049	0.961	-4.91e-05	5.16e-05
dltt	3.781e-05	3.82e-05	0.990	0.322	-3.71e-05	0.000
dp	-0.0002	0.000	-1.293	0.196	-0.000	8.17e-05
ib	-0.0001	0.000	-1.035	0.300	-0.000	9.88e-05
invt	-0.0001	7.07e-05	-1.537	0.124	-0.000	2.99e-05
ivao	2.692e-06	1.79e-05	0.151	0.880	-3.23e-05	3.77e-05
ivst	-8.048e-05	7.87e-05	-1.023	0.306	-0.000	7.38e-05
lct	-0.0001	7.15e-05	-1.574	0.116	-0.000	2.76e-05
lt	-4.851e-05	7.56e-05	-0.642	0.521	-0.000	9.96e-05
ni	-3.683e-06	8.77e-05	-0.042	0.967	-0.000	0.000
ppegt	-1.801e-06	7.8e-06	-0.231	0.817	-1.71e-05	1.35e-05
pstk	-9.442e-05	0.000	-0.348	0.728	-0.001	0.000
re	-1.27e-05	7.89e-06	-1.611	0.107	-2.82e-05	2.75e-06
rect	-0.0001	6.69e-05	-1.628	0.103	-0.000	2.22e-05
sale	1.285e-05	2.03e-05	0.632	0.527	-2.7e-05	5.27e-05
sstk	0.0002	5.15e-05	3.466	0.001	7.75e-05	0.000
txp	6.482e-05	0.000	0.310	0.756	-0.000	0.000
txt	-1.053e-05	0.000	-0.089	0.929	-0.000	0.000
xint	0.0012	0.000	4.746	0.000	0.001	0.002
prcc_f	0.0010	0.000	3.998	0.000	0.001	0.001
dch_wc	-0.9484	0.372	-2.547	0.011	-1.678	-0.218
ch_rsst	0.9954	0.286	3.482	0.000	0.435	1.556
dch_rec	2.1294	0.472	4.511	0.000	1.204	3.055
dch_inv	1.3559	0.654	2.074	0.038	0.075	2.637
soft_assets	1.8267	0.154	11.826	0.000	1.524	2.129
dpi	0.0484	0.078	0.617	0.537	-0.105	0.202
ch_cs	0.0594	0.026	2.266	0.023	0.008	0.111
ch_cm	-0.0030	0.015	-0.200	0.842	-0.032	0.026
ch_roa	-0.4986	0.220	-2.270	0.023	-0.929	-0.068
ch_fcf	0.4263	0.240	1.779	0.075	-0.043	0.896
reoa	0.2248	0.040	5.684	0.000	0.147	0.302
EBIT	-0.4205	0.138	-3.039	0.002	-0.692	-0.149
issue	1.1626	0.185	6.296	0.000	0.801	1.524
bm	-0.0637	0.034	-1.891	0.059	-0.130	0.002

Significant Variables (p < 0.05): act, ap, che, cogs, dlc, invt, rect, sstk, xint, prcc_f, ch_rsst, dch_rec, soft_assets, reoa, EBIT, issue

Not Significant Variables (p >= 0.05): at, ceq, csho, dltis, dltt, dp, ib, ivao, ivst, lct, lt, ni, ppegt, pstk, re, sale, txp, txt, dch_wc, dch_inv, dpi, ch_cs, ch_cm, ch_roa, ch_fcf, bm

In [28]:

```
predicted_fraud = logit_res_fraud.predict(X_fraud)
predicted_fraud
```

Out[28]:

```
0         0.004817
1         0.003891
2         0.006725
3         0.011058
4         0.003455
            ...
146039    0.002191
146040    0.012277
146041    0.017714
146042    0.011264
146044    0.003752
Length: 126483, dtype: float64
```

In [29]:

```
predicted_classes_fraud = (predicted_fraud >= 0.5).astype(int)
predicted_classes_fraud[:97613]
```

Out[29]:

```
0         0
1         0
2         0
3         0
4         0
         ..
111354    0
111355    0
111356    0
111357    0
111358    0
Length: 97613, dtype: int64
```

In [30]:

```
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix

# Assuming y_14 and predicted_classes_14 are defined elsewhere
accuracy_fraud = accuracy_score(y_fraud['misstate'], predicted_classes_fraud)
conf_matrix_fraud = confusion_matrix(y_fraud['misstate'], predicted_classes_fraud)

classification_report_str_fraud = classification_report(y_fraud['misstate'], predicted_classes_fraud)


# Optionally, print or use these metrics as needed
print("Accuracy:", accuracy_fraud)
print("Confusion Matrix:", conf_matrix_fraud)
print("Classification Report:", classification_report_str_fraud)
```

```
Accuracy: 0.9928369820450179
Confusion Matrix: [[125573      1]
 [   905      4]]
Classification Report:               precision    recall  f1-score   support

         0.0       0.99      1.00      1.00    125574
         1.0       0.80      0.00      0.01       909

    accuracy                           0.99    126483
   macro avg       0.90      0.50      0.50    126483
weighted avg       0.99      0.99      0.99    126483
```

The model achieved 99.15% accuracy, correctly identifying negative cases but struggling with positive ones. It had high precision and recall for the majority class (class 0) but performed poorly for the minority class (class 1). This indicates a need to address class imbalance and improve performance for the minority class.

Comparing the accuracy rates provided in the three accuracy reports:

Model using 28 raw accounting variables: Accuracy: 0.9915063410764079 Model using 14 financial ratio variables: Accuracy: 0.9915063410764079 Model using all 42 variables (28 + 14): Accuracy: 0.9914713397346898 All three models have very similar accuracy rates, with the difference being minimal. However, if we strictly consider the accuracy metric, the model using 28 raw accounting variables or the model using 14 financial ratio variables seems to have a slightly higher accuracy compared to the model using all 42 variables.