

▼ Final Project

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Aim of the Project

Undertake a financial/accounting analysis of a large set of U.S. companies during 5 key stock market crashes over the past few decades and explain determinants of stock returns.

1. **1987 Stock Market Crash** (Sept 1987 – Dec 1987)
2. **Dot Com Bubble and Crash** (Jan 2000 – Oct 2002)
3. **Great Recession & Financial Crisis** (Jan 2008 – Feb 2009)
4. **The Covid Shock** (Feb 2020 – March 2020)
5. **“The End of Easy Money”**(Jan 2022 – Sep 2022)

```
#Importing the necessary libraries and packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import statsmodels.api as sm
```

```
#mounting the drive
from google.colab import drive
drive.mount('/gdrive')
```

Drive already mounted at /gdrive; to attempt to forcibly remount, call drive.mou

▼ Uploading the G Sector Files

```
gsector_1987 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/GSECTOR-1986.csv')
gsector_2001 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/GSECTOR-2000.csv')
gsector_2008 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/GSECTOR-2007.csv')
gsector_2020 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/GSECTOR-2019.csv')
gsector_2022 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/GSECTOR-2021.csv')
```

An explanation of the G-Sectors is given as below:

10.0 Energy

15.0 Materials

20.0 Industrials

25.0 Consumer Discretionary

30.0 Consumer Staples

35.0 Health Care

40.0 Financials

45.0 Information Technology

50.0 Communication Services

55.0 Utilities

60.0 Real Estate

```
gsector_1987.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7219 entries, 0 to 7218
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype
---  -
 0   gvkey       7219 non-null   int64
 1   fyear       7219 non-null   int64
 2   TICKER      7219 non-null   object
 3   gsector     7210 non-null   float64
dtypes: float64(1), int64(2), object(1)
memory usage: 225.7+ KB
```

▼ Uploading files containing financial ratios

These files have been derived from assignment 3

```
ratios_1987 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/financial_ratios_19
ratios_2001 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/financial_ratios_20
ratios_2008 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/financial_ratios_20
ratios_2020 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/financial_ratios_20
ratios_2022 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/financial_ratios_20
```

These files contain various financial ratios for each of the stock market crashes and the average returns for those crashes. The following analysis has already been performed on these datasets in Assignment 3 for the purpose of calculating regression.

1. **Merging Data** Merging financial data with average returns for the months leading up to the 5 stock market crashes.

2. **Treating Missing Values** Running logistic regression for Current Assets, Current Liabilities, Total Liabilities, Long-Term Debt, Cost of Goods Sold, and Retained Earnings.
3. **Calculating financial ratios** Calculating financial ratios like Net Profit Margin, Gross Profit Margin, Liquidity ratio, Leverage, Debt/Total Assets, Asset Turnover Ratio, and ROE.
4. **Regression** Regressing various financial ratios on average returns and interpreting the results.

```
ratios_1987.head()
```

	consol	popsrc	datafmt	TICKER	curcd	act	...	RET	Net Profit Margin	Gross Profit Margin	1
.	C	D	STD	ANTQ	USD	13.090	...	-0.126467	0.021841	0.473422	
.	C	D	STD	AIR	USD	168.950	...	-0.058069	0.051514	0.247015	
.	C	D	STD	ACSE	USD	2.385	...	-0.069427	-0.145579	-0.006851	
.	C	D	STD	AECE	USD	18.715	...	0.014061	0.015301	0.360856	
.	C	D	STD	AELNA	USD	52.080	...	-0.099851	0.030642	0.263189	

▼ Uploading files containing the FF output for 5 years

These files have been derived from assignment 2

```
ff_1987 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/FF-Output-1983-1987.csv')
ff_2001 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/FF-Output-1997-2001.csv')
ff_2008 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/FF-Output-2004-2008.csv')
ff_2020 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/FF-Output-2016-2020.csv')
ff_2022 = pd.read_csv(r'/gdrive/MyDrive/Finance Final Project/FF-Output-2018-2022.csv')
```

```
ff_1987.head()
```

	Unnamed: 0	TICKER	const	mktrf	smb	hml
0	1	CNK	0.008628	0.881037	0.581720	-0.000531
1	2	GENE	0.038865	1.157391	1.382452	-1.254665
2	3	GAMA	-0.005431	0.772968	-0.073854	0.189572
3	4	TCOMA	0.029071	0.926688	0.038847	-1.166874



▼ 1987 Stock Market Crash

The stock market crash of 1987, also known as Black Monday, occurred on October 19th, 1987. The crash was a sudden and severe drop in stock prices, with the Dow Jones Industrial Average falling by over 22% in one day. The crash was caused by a combination of factors, including overvalued stocks, a decline in international markets, and computerized trading programs.

▼ Merging the three files together

```
# Renaming tic to TICKER in the gsector file
gsector_1987 = gsector_1987.rename(columns={'tic': 'TICKER'})

# Merge the DataFrames based on the 'TICKER' column
merged_df = pd.merge(gsector_1987, ratios_1987, on='TICKER')
merged_df = pd.merge(merged_df, ff_1987, on='TICKER')

merged_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 880 entries, 0 to 879
Data columns (total 38 columns):
#   Column              Non-Null Count  Dtype
---  -
0   gvkey_x              880 non-null    int64
1   fyear_x              880 non-null    int64
2   TICKER               880 non-null    object
3   gsector              880 non-null    float64
4   gvkey_y              880 non-null    int64
5   datadate             880 non-null    object
6   fyear_y              880 non-null    int64
7   indfmt               880 non-null    object
8   consol              880 non-null    object
9   popsrc               880 non-null    object
10  datafmt              880 non-null    object
11  curcd                880 non-null    object
12  act                  880 non-null    float64
```

```

13  at                880 non-null    float64
14  che                880 non-null    float64
15  cogs                880 non-null    float64
16  dlтт                880 non-null    float64
17  lct                880 non-null    float64
18  lt                 880 non-null    float64
19  ni                 880 non-null    float64
20  re                 880 non-null    float64
21  sale               880 non-null    float64
22  costat             880 non-null    object
23  RET                880 non-null    float64
24  Net Profit Margin  880 non-null    float64
25  Gross Profit Margin 880 non-null    float64
26  Total Debt/Equity   880 non-null    float64
27  Return on Equity    880 non-null    float64
28  Liquidity           880 non-null    float64
29  ROA                880 non-null    float64
30  Debt/Total Assets   880 non-null    float64
31  Asset Turnover Ratio 880 non-null    float64
32  at_log              880 non-null    float64
33  Unnamed: 0          880 non-null    int64
34  const               880 non-null    float64
35  mktrf               880 non-null    float64
36  smb                 880 non-null    float64
37  hml                 880 non-null    float64
dtypes: float64(25), int64(5), object(8)
memory usage: 268.1+ KB

```

```

# Getting a sense of industry indicators
sector_counts = merged_df.groupby('gsector').size()
sector_counts

```

```

gsector
10.0    52
15.0    66
20.0   211
25.0   147
30.0    60
35.0    67
40.0    77
45.0   117
50.0    14
55.0    56
60.0    13
dtype: int64

```

▼ Run OLS regression with the following three main categories

1. **Risk Exposures:** This included systematic risk (market risk), SML (Small Minus Big), which is the size risk, and HML (High minus Low), which is the Value vs Growth risk.

2. **Financial Ratios:** This includes various financial ratios, including but not limited to Liquidity, Leverage, Asset Turnover Ratio, Net and Gross Profit Margin, ROE and ROA.
3. **Industry Indicators:** This indicates which industries had the highest amount of affect on stock returns.

▼ 1987- Regression 1

Regression using all 3 Categories

```
# General regression code:
X1 = merged_df[['Gross Profit Margin', 'Debt/Total Assets', 'Asset Turnover Ratio', '
X2 = pd.get_dummies(merged_df['gsector'], prefix='sector')
X3 = merged_df[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2, X3], axis=1)

y = merged_df['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())
```

OLS Regression Results					
=====					
Dep. Variable:	RET	R-squared:	0.242		
Model:	OLS	Adj. R-squared:	0.227		
Method:	Least Squares	F-statistic:	16.20		
Date:	Sat, 06 May 2023	Prob (F-statistic):	1.39e-41		
Time:	12:27:41	Log-Likelihood:	1397.9		
No. Observations:	880	AIC:	-2760.		
Df Residuals:	862	BIC:	-2674.		
Df Model:	17				
Covariance Type:	nonrobust				
=====					
	coef	std err	t	P> t	[0.025

const	-0.0087	0.008	-1.151	0.250	-0.024
Gross Profit Margin	0.0145	0.006	2.488	0.013	0.003
Debt/Total Assets	-0.0326	0.009	-3.500	0.000	-0.051
Asset Turnover Ratio	0.0066	0.003	2.425	0.016	0.001
at_log	0.0019	0.001	1.858	0.064	-0.000
sector_10.0	-0.0190	0.007	-2.734	0.006	-0.033
sector_15.0	0.0180	0.006	2.921	0.004	0.006
sector_20.0	0.0046	0.004	1.138	0.255	-0.003
sector_25.0	-0.0103	0.005	-2.176	0.030	-0.020

sector_30.0	-0.0032	0.007	-0.438	0.661	-0.018
sector_35.0	-0.0048	0.006	-0.783	0.434	-0.017
sector_40.0	-0.0019	0.007	-0.288	0.773	-0.015
sector_45.0	-0.0142	0.005	-2.610	0.009	-0.025
sector_50.0	-0.0012	0.012	-0.096	0.924	-0.026
sector_55.0	0.0046	0.007	0.646	0.518	-0.009
sector_60.0	0.0186	0.013	1.443	0.149	-0.007
mktrf	-0.0552	0.005	-11.793	0.000	-0.064
smb	-0.0088	0.002	-3.987	0.000	-0.013
hml	0.0031	0.003	1.203	0.229	-0.002

Omnibus:	39.819	Durbin-Watson:	1.871
Prob(Omnibus):	0.000	Jarque-Bera (JB):	120.916
Skew:	-0.040	Prob(JB):	5.54e-27
Kurtosis:	4.814	Cond. No.	8.47e+16

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly
- [2] The smallest eigenvalue is 4.49e-30. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

The regression model shows the relationship between the dependent variable, RET(stock returns), and various independent variables. The R-squared value suggests that 24.2% of the variance in the dependent variable is explained by the model, with an adjusted R-Squared. The coefficients of the independent variables show their impact on the dependent variable, with Gross Profit Margin, Debt/Total Assets, Asset Turnover Ratio, sector_10.0, sector_15.0, sector_25.0, sector_45.0, mktrf, and smb having statistically significant impacts. The model has some potential issues with multicollinearity and singularity, therefore, further regressions are performed to reduce such issues.

▼ 1987- Regression 2

Regression using only financial ratios and industry indicators

```
# General regression code:
X1 = merged_df[['Gross Profit Margin', 'Debt/Total Assets', 'Asset Turnover Ratio', '
X2 = pd.get_dummies(merged_df['gsector'], prefix='sector')

X = pd.concat([X1, X2], axis=1)

y = merged_df['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
```

```
# list regression output
print(model.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          RET      R-squared:                0.109
Model:                  OLS      Adj. R-squared:           0.095
Method:                 Least Squares      F-statistic:          7.574
Date:                  Sat, 06 May 2023      Prob (F-statistic):    3.46e-15
Time:                  12:27:41      Log-Likelihood:       1326.7
No. Observations:      880      AIC:                  -2623.
Df Residuals:          865      BIC:                  -2552.
Df Model:              14
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	-0.0507	0.007	-7.376	0.000	-0.064
Gross Profit Margin	0.0193	0.006	3.086	0.002	0.007
Debt/Total Assets	-0.0501	0.010	-5.156	0.000	-0.069
Asset Turnover Ratio	0.0070	0.003	2.406	0.016	0.001
at_log	0.0013	0.001	1.436	0.151	-0.000
sector_10.0	-0.0306	0.007	-4.205	0.000	-0.045
sector_15.0	0.0101	0.007	1.536	0.125	-0.003
sector_20.0	-0.0050	0.004	-1.172	0.242	-0.013
sector_25.0	-0.0218	0.005	-4.394	0.000	-0.032
sector_30.0	-0.0012	0.008	-0.152	0.879	-0.017
sector_35.0	-0.0139	0.007	-2.122	0.034	-0.027
sector_40.0	-0.0034	0.007	-0.478	0.632	-0.017
sector_45.0	-0.0298	0.005	-5.659	0.000	-0.040
sector_50.0	-0.0053	0.013	-0.396	0.692	-0.032
sector_55.0	0.0281	0.007	3.885	0.000	0.014
sector_60.0	0.0220	0.014	1.575	0.116	-0.005

```

=====
Omnibus:                35.762      Durbin-Watson:          1.952
Prob(Omnibus):          0.000      Jarque-Bera (JB):       90.834
Skew:                   -0.140      Prob(JB):               1.89e-20
Kurtosis:               4.549      Cond. No.                7.20e+16
=====

```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly
- [2] The smallest eigenvalue is 6.03e-30. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

The OLS regression model suggests that Gross Profit Margin, Debt/Total Assets, Asset Turnover Ratio, and some industry sectors have significant effects on the stock returns of the companies in the sample. However, the overall explanatory power of the model is weak, as indicated by the low R-squared value of 10.9%, and an adjusted R-Squared value 9.5%. Additionally, there may be issues of multicollinearity, and the design matrix may be singular, which could affect the reliability of the coefficient estimates. As risk exposures were excluded, the R2 dropped significantly indicating that 13.3% variance in the model is explained by risk exposures.

▼ 1987- Regression 3

Regression using only financial ratios and risk exposures

```
# General regression code:
X1 = merged_df[['Gross Profit Margin', 'Debt/Total Assets', 'Asset Turnover Ratio', '
X2 = merged_df[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2], axis=1)

y = merged_df['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  RET      R-squared:                  0.213
Model:                          OLS      Adj. R-squared:              0.207
Method:                        Least Squares      F-statistic:                33.81
Date:                          Sat, 06 May 2023      Prob (F-statistic):        8.75e-42
Time:                          12:27:41      Log-Likelihood:            1381.5
No. Observations:              880      AIC:                       -2747.
Df Residuals:                  872      BIC:                       -2709.
Df Model:                      7
Covariance Type:               nonrobust
=====
                                coef      std err          t      P>|t|      [0.025
-----
const                -0.0114      0.008      -1.431      0.153      -0.027
Gross Profit Margin    0.0130      0.006       2.241      0.025       0.002
Debt/Total Assets     -0.0309      0.009      -3.527      0.000      -0.048
Asset Turnover Ratio   0.0069      0.002       3.051      0.002       0.002
at_log                0.0025      0.001       2.531      0.012       0.001
mktrf                -0.0586      0.004     -13.411      0.000      -0.067
smb                  -0.0097      0.002      -4.595      0.000      -0.014
hml                   0.0045      0.002       1.947      0.052     -3.57e-05
=====
Omnibus:                 36.429      Durbin-Watson:              1.895
Prob(Omnibus):           0.000      Jarque-Bera (JB):           102.648
Skew:                   -0.059      Prob(JB):                   5.13e-23
Kurtosis:                4.669      Cond. No.                   33.5
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is a multiple linear regression with seven independent variables. The dependent variable is the RET (stock returns) and the independent variables are Gross Profit Margin, Debt/Total Assets, Asset Turnover Ratio, at_log, mktrf, smb, and hml. The R-squared value is 0.213, indicating that the model explains 21.3% of the variance in the dependent variable, with an adjusted R-Squared of 20.7%. The t-tests and p-values indicate the statistical significance of the coefficients. The regression suggests that Gross Profit Margin, Debt/Total Assets, Asset Turnover Ratio, at_log, mktrf, and smb have significant impact on the return, while hml is borderline significant. This regression dropped the financial ratios, indicating that 2.9% of the variance was explained by the financial ratios.

▼ 1987- Regression 4

Regression using only risk exposure

```
#General regression code:
X = merged_df[['mktrf', 'smb', 'hml']]
y = merged_df['RET']
# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
```

```
#list regression output
print(model.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  RET    R-squared:                  0.191
Model:                            OLS    Adj. R-squared:             0.188
Method:                 Least Squares    F-statistic:                 68.74
Date:                  Sat, 06 May 2023    Prob (F-statistic):         6.36e-40
Time:                  12:27:41    Log-Likelihood:             1368.9
No. Observations:                  880    AIC:                        -2730.
Df Residuals:                      876    BIC:                        -2711.
Df Model:                          3
Covariance Type:                  nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          -0.0006      0.005      -0.118      0.906      -0.010      0.009
mktrf          -0.0581      0.004     -13.287      0.000      -0.067     -0.050
smb            -0.0120      0.002      -6.493      0.000      -0.016     -0.008
hml             0.0015      0.002       0.649      0.516      -0.003      0.006
=====
Omnibus:                 45.581    Durbin-Watson:              1.911
Prob(Omnibus):            0.000    Jarque-Bera (JB):           129.833

```

Skew:	-0.190	Prob(JB):	6.41e-29
Kurtosis:	4.843	Cond. No.	6.13
=====			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is a regression model with three independent variables, namely mktrf, smb, and hml for the risk exposures, and a dependent variable RET (stock returns). The model has an R-squared value of 0.191, indicating that the independent variables explain approximately 19.1% of the variance in the dependent variable, with an adjuted R-Squared of 18.8%. The coefficients of the independent variables suggest that mktrf and smb have negative relationships with RET, while hml has a positive relationship. Overall, the model can be used to predict the value of RET based on the values of the independent variables.

▼ 1987- Regression 5

Regression using only industry indicators

```
X_all_sectors = pd.get_dummies(merged_df['gsector'], prefix='sector')
y = merged_df['RET']
# Perform the regression using statsmodels
model_all_sectors = sm.OLS(y, X_all_sectors).fit()

# Identify the industry with the coefficient value closest to zero
reference_sector = model_all_sectors.params.abs().idxmin()

print(reference_sector)

sector_60.0

# Create dummy variables for the industry sectors
X_all_sectors = pd.get_dummies(merged_df['gsector'], prefix='sector')
y = merged_df['RET']

# Exclude the reference sector's dummy variable from the independent variables
X = X_all_sectors.drop(columns=[reference_sector])

# Add a constant to the independent variables
X = sm.add_constant(X)

# Perform the regression using statsmodels without the reference sector's dummy varia
model_5 = sm.OLS(y, X).fit()
```

```
# Print the regression output
print(model_5.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.068
Model:                  OLS      Adj. R-squared:         0.057
Method:                 Least Squares      F-statistic:          6.311
Date:                   Sat, 06 May 2023    Prob (F-statistic):    2.15e-09
Time:                   12:30:28      Log-Likelihood:        1306.7
No. Observations:       880      AIC:                  -2591.
Df Residuals:           869      BIC:                  -2539.
Df Model:               10
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025	0.975]
const	-0.0346	0.015	-2.259	0.024	-0.065	-0.005
sector_10.0	-0.0533	0.017	-3.115	0.002	-0.087	-0.020
sector_15.0	-0.0079	0.017	-0.472	0.637	-0.041	0.025
sector_20.0	-0.0245	0.016	-1.554	0.121	-0.055	0.006
sector_25.0	-0.0406	0.016	-2.543	0.011	-0.072	-0.009
sector_30.0	-0.0124	0.017	-0.736	0.462	-0.046	0.021
sector_35.0	-0.0288	0.017	-1.720	0.086	-0.062	0.004
sector_40.0	-0.0406	0.017	-2.453	0.014	-0.073	-0.008
sector_45.0	-0.0443	0.016	-2.745	0.006	-0.076	-0.013
sector_50.0	-0.0296	0.021	-1.394	0.164	-0.071	0.012
sector_55.0	-0.0013	0.017	-0.074	0.941	-0.035	0.032

```

=====
Omnibus:                46.203      Durbin-Watson:          1.975
Prob(Omnibus):           0.000      Jarque-Bera (JB):       112.406
Skew:                    -0.268      Prob(JB):               3.90e-25
Kurtosis:                4.667      Cond. No.:              29.4
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

The regression model examines the relationship between the stock returns (dependent variable) and industry sectors (independent variables) using Ordinary Least Squares (OLS) method.

The initial model includes dummy variables for all industry sectors, and the industry with the coefficient value closest to zero is identified as the reference sector. Then, a new model is created by excluding the reference sector's dummy variable from the independent variables.

The final model shows that the adjusted R-squared value is 0.057, indicating that the independent variables can explain 5.7% of the variation in the dependent variable.

Among the remaining industry sectors, the coefficients for sectors 10, 25, 40, and 45 are statistically significant at the 5% level, indicating that these sectors have a significant impact on stock returns. The coefficient for sector 15 is not statistically significant. The negative coefficients

for all significant sectors suggest that stocks in these sectors have a negative impact on returns. The intercept coefficient is also negative and statistically significant, indicating that the expected return is negative even when all the independent variables are zero.

▼ 1987- Conclusion

Thus we note that the maximum variability in the data is explained by the risk exposure

This too in this case, by the systematic risk and the size risk(Small minus Big).

▼ Dot Com Bubble and Crash

The dot com bubble crash of 2001 was a significant market downturn in the technology sector, fueled by the excessive speculation and overvaluation of internet-related stocks. This bubble began to burst in March 2000, leading to a sharp decline in stock prices of companies in the technology industry. By 2001, many dot com companies went bankrupt, resulting in massive job losses and a decline in overall economic growth. The crash was a painful reminder of the risks associated with speculative bubbles and market irrationality.

▼ Merging the three files together

```
# Renaming tic to TICKER in the gsector file
gsector_2001 = gsector_2001.rename(columns={'tic': 'TICKER'})

# Merge the DataFrames based on the 'TICKER' column
merged_df_2001 = pd.merge(gsector_2001, ratios_2001, on='TICKER')
merged_df_2001 = pd.merge(merged_df_2001, ff_2001, on='TICKER')
```

```
merged_df_2001.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1973 entries, 0 to 1972
Data columns (total 38 columns):
#   Column              Non-Null Count  Dtype
---  -
0   gvkey_x              1973 non-null   int64
1   fyear_x              1973 non-null   int64
2   TICKER               1973 non-null   object
3   gsector              1972 non-null   float64
```

```

4   gvkey_y      1973 non-null    int64
5   datadate     1973 non-null    object
6   fyear_y      1973 non-null    int64
7   indfmt       1973 non-null    object
8   consol       1973 non-null    object
9   popsrc       1973 non-null    object
10  datafmt      1973 non-null    object
11  curcd        1973 non-null    object
12  act          1973 non-null    float64
13  at           1973 non-null    float64
14  che          1973 non-null    float64
15  cogs         1973 non-null    float64
16  dltd         1973 non-null    float64
17  lct          1973 non-null    float64
18  lt           1973 non-null    float64
19  ni           1973 non-null    float64
20  re           1973 non-null    float64
21  sale         1973 non-null    float64
22  costat       1973 non-null    object
23  RET          1973 non-null    float64
24  at_log       1973 non-null    float64
25  Net Profit Margin  1973 non-null    float64
26  Gross Profit Margin 1973 non-null    float64
27  Total Debt/Equity  1973 non-null    float64
28  Return on Equity   1973 non-null    float64
29  Liquidity          1973 non-null    float64
30  ROA                1973 non-null    float64
31  Debt/Total Assets  1973 non-null    float64
32  Asset Turnover Ratio 1973 non-null    float64
33  Unnamed: 0         1973 non-null    int64
34  const              1973 non-null    float64
35  mktrf              1973 non-null    float64
36  smb                1973 non-null    float64
37  hml                1973 non-null    float64
dtypes: float64(25), int64(5), object(8)
memory usage: 601.1+ KB

```

▼ Run OLS regression with the following three main categories

1. **Risk Exposures:** This included systematic risk (market risk), SML (Small Minus Big), which is the size risk, and HML (High minus Low), which is the Value vs Growth risk.
2. **Financial Ratios:** This includes various financial ratios, including but not limited to Liquidity, Leverage, Asset Turnover Ratio, Net and Gross Profit Margin, ROE and ROA.
3. **Industry Indicators:** This indicates which industries had the highest amount of affect on stock returns.

▼ 2001- Regression 1

Regression using industry indicators, financial ratios and risk exposures.

```
# General regression code:
X1 = merged_df_2001[['Net Profit Margin', 'Gross Profit Margin', 'ROA', 'Debt/Total A
X2 = pd.get_dummies(merged_df_2001['gsector'], prefix='sector')
X3 = merged_df_2001[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2, X3], axis=1)

y = merged_df_2001['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())
```

OLS Regression Results					
=====					
Dep. Variable:	RET	R-squared:	0.352		
Model:	OLS	Adj. R-squared:	0.346		
Method:	Least Squares	F-statistic:	55.87		
Date:	Sat, 06 May 2023	Prob (F-statistic):	2.62e-168		
Time:	12:27:41	Log-Likelihood:	3203.7		
No. Observations:	1973	AIC:	-6367.		
Df Residuals:	1953	BIC:	-6256.		
Df Model:	19				
Covariance Type:	nonrobust				
=====					
	coef	std err	t	P> t	[0.025

const	0.0180	0.048	0.374	0.708	-0.076
Net Profit Margin	-0.0027	0.002	-1.423	0.155	-0.006
Gross Profit Margin	0.0057	0.003	2.244	0.025	0.001
ROA	-0.0017	0.008	-0.228	0.819	-0.017
Debt/Total Assets	0.0071	0.005	1.316	0.188	-0.004
Asset Turnover Ratio	0.0039	0.002	2.297	0.022	0.001
sector_10.0	-0.0091	0.048	-0.188	0.851	-0.104
sector_15.0	-0.0208	0.048	-0.431	0.667	-0.115
sector_20.0	-0.0253	0.048	-0.526	0.599	-0.120
sector_25.0	-0.0111	0.048	-0.232	0.817	-0.106
sector_30.0	-0.0109	0.048	-0.225	0.822	-0.106
sector_35.0	-0.0069	0.048	-0.143	0.887	-0.101
sector_40.0	-0.0111	0.048	-0.231	0.817	-0.105
sector_45.0	-0.0235	0.048	-0.488	0.626	-0.118
sector_50.0	-0.0156	0.049	-0.320	0.749	-0.111
sector_55.0	-0.0162	0.048	-0.335	0.738	-0.111
sector_60.0	-0.0207	0.048	-0.428	0.669	-0.116
mktrf	-0.0225	0.002	-10.815	0.000	-0.027
smb	-0.0008	0.001	-0.584	0.559	-0.004
hml	0.0350	0.002	22.916	0.000	0.032
=====					

Omnibus:	341.383	Durbin-Watson:	2.051
Prob(Omnibus):	0.000	Jarque-Bera (JB):	2043.791
Skew:	0.671	Prob(JB):	0.00
Kurtosis:	7.802	Cond. No.	312.

=====

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

The regression model examines the relationship between stock returns (RET) and various independent variables. The R-squared value of 0.352 indicates that 35.2% of the variance in the dependent variable is explained by the model, with an adjusted R-squared of 0.346. The coefficients of the independent variables indicate that Gross Profit Margin, Debt/Total Assets, Asset Turnover Ratio, sector_10.0, sector_15.0, sector_25.0, sector_45.0, mktrf, and hml have a statistically significant impact on the dependent variable. However, the model may have some issues with multicollinearity and singularity, and further regressions are required to address these issues.

▼ 2001- Regression 2

Regression using only industry indicators and risk exposure

```
# General regression code:
X1 = pd.get_dummies(merged_df_2001['gsector'], prefix='sector')
X2 = merged_df_2001[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2], axis=1)

y = merged_df_2001['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          RET      R-squared:          0.348
Model:                  OLS      Adj. R-squared:       0.343
Method:                 Least Squares      F-statistic:       74.58
Date:                  Sat, 06 May 2023      Prob (F-statistic): 4.29e-170
Time:                  12:27:41      Log-Likelihood:    3197.1
No. Observations:      1973      AIC:               -6364.
Df Residuals:          1958      BIC:               -6280.
Df Model:              14
Covariance Type:       nonrobust
```


	coef	std err	t	P> t	[0.025	0.975]
const	0.0275	0.048	0.572	0.567	-0.067	0.122
sector_10.0	-0.0093	0.048	-0.193	0.847	-0.104	0.085
sector_15.0	-0.0210	0.048	-0.435	0.663	-0.116	0.074
sector_20.0	-0.0239	0.048	-0.496	0.620	-0.118	0.071
sector_25.0	-0.0088	0.048	-0.183	0.855	-0.103	0.086
sector_30.0	-0.0078	0.048	-0.162	0.871	-0.103	0.087
sector_35.0	-0.0084	0.048	-0.174	0.862	-0.103	0.086
sector_40.0	-0.0118	0.048	-0.246	0.806	-0.106	0.083
sector_45.0	-0.0217	0.048	-0.450	0.653	-0.116	0.073
sector_50.0	-0.0152	0.049	-0.312	0.755	-0.111	0.080
sector_55.0	-0.0173	0.048	-0.358	0.721	-0.112	0.078
sector_60.0	-0.0236	0.048	-0.487	0.627	-0.119	0.071
mktrf	-0.0229	0.002	-11.007	0.000	-0.027	-0.019
smb	-0.0016	0.001	-1.146	0.252	-0.004	0.001
hml	0.0358	0.001	24.337	0.000	0.033	0.039
=====						
Omnibus:		372.905	Durbin-Watson:			2.049
Prob(Omnibus):		0.000	Jarque-Bera (JB):			2388.177
Skew:		0.728	Prob(JB):			0.00
Kurtosis:		8.190	Cond. No.			255.
=====						

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is an OLS regression summary, showing the results of a regression model that estimates the relationship between the dependent variable "RET" and the independent variables "const", "sector_10.0", "sector_15.0", "sector_20.0", "sector_25.0", "sector_30.0", "sector_35.0", "sector_40.0", "sector_45.0", "sector_50.0", "sector_55.0", "sector_60.0", "mktrf", "smb", and "hml".

The R-squared value of 0.348 indicates that 34.8% of the variance in the dependent variable is explained by the independent variables. The adjusted R-squared value of 0.343 is slightly lower, indicating that the model has not overfit the data.

Removing financial ratios from the regression reduced 0.4% explanatory power from the regression.

▼ 2001- Regression 3

Regression using only risk exposure and financial ratios

```
# General regression code:
```

```
X1 = merged_df_2001[['Net Profit Margin', 'Gross Profit Margin', 'ROA', 'Debt/Total A
X2 = merged_df_2001[['mktrf', 'smb', 'hml']]
```

```
X = pd.concat([X1, X2], axis=1)
```

```

y = merged_df_2001['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())

```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.340
Model:                  OLS      Adj. R-squared:     0.338
Method:                 Least Squares      F-statistic:       126.7
Date:                  Sat, 06 May 2023      Prob (F-statistic): 2.21e-171
Time:                  12:27:41      Log-Likelihood:    3186.0
No. Observations:      1973      AIC:               -6354.
Df Residuals:          1964      BIC:               -6304.
Df Model:               8
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	0.0041	0.004	1.001	0.317	-0.004
Net Profit Margin	-0.0028	0.002	-1.511	0.131	-0.006
Gross Profit Margin	0.0051	0.003	2.026	0.043	0.000
ROA	-0.0013	0.008	-0.166	0.868	-0.016
Debt/Total Assets	0.0086	0.005	1.810	0.070	-0.001
Asset Turnover Ratio	0.0027	0.001	1.977	0.048	2.12e-05
mktrf	-0.0244	0.002	-12.750	0.000	-0.028
smb	-0.0013	0.001	-0.956	0.339	-0.004
hml	0.0363	0.001	27.187	0.000	0.034

```

=====
Omnibus:                328.717      Durbin-Watson:        2.050
Prob(Omnibus):           0.000      Jarque-Bera (JB):     1877.112
Skew:                    0.654      Prob(JB):              0.00
Kurtosis:                7.596      Cond. No.              14.9
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is an OLS regression summary, showing the results of a regression model that estimates the relationship between the dependent variable "RET" and the independent variables "const", "Net Profit Margin", "Gross Profit Margin", "ROA", "Debt/Total Assets", "Asset Turnover Ratio", "mktrf", "smb", and "hml".

The R-squared value of 0.340 indicates that 34.0% of the variance in the dependent variable is explained by the independent variables. The adjusted R-squared value of 0.338 is slightly lower, indicating that the model has not overfit the data.

Removing gsector indicators reduced the explanatory power by only 0.8%.

▼ 2001- Regression 4

Regression using only risk exposure

```
#General regression code:
X = merged_df_2001[['mktrf', 'smb', 'hml']]
y = merged_df_2001['RET']
# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
```

```
#list regression output
print(model.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.337
Model:                  OLS      Adj. R-squared:       0.336
Method:                 Least Squares      F-statistic:        333.4
Date:                  Sat, 06 May 2023      Prob (F-statistic):  4.81e-175
Time:                  12:27:41      Log-Likelihood:     3180.7
No. Observations:      1973      AIC:                -6353.
Df Residuals:          1969      BIC:                -6331.
Df Model:               3
Covariance Type:       nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.0134      0.002       6.440      0.000      0.009      0.017
mktrf         -0.0244      0.002     -12.906      0.000     -0.028     -0.021
smb           -0.0020      0.001      -1.518      0.129     -0.005      0.001
hml            0.0369      0.001     29.902      0.000      0.034      0.039
=====
Omnibus:          355.132      Durbin-Watson:       2.048
Prob(Omnibus):    0.000      Jarque-Bera (JB):    2138.395
Skew:             0.703      Prob(JB):            0.00
Kurtosis:         7.902      Cond. No.            3.90
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is a multiple linear regression model with three independent variables: mktrf, smb, and hml. The dependent variable is RET. The model has a significant overall fit with an R-squared of 0.337, meaning 33.7% of the variance in RET is explained by the three independent variables. The coefficients for mktrf and hml are significant at the 0.05 level, while the coefficient for smb is not

significant at the 0.05 level. The model's intercept is also significant at the 0.05 level. The model assumes that the covariance matrix of the errors is correctly specified.

▼ 2001- Regression 5

This regression only takes into account the industry indicators.

```
X_all_sectors = pd.get_dummies(merged_df_2001['gsector'], prefix='sector')
y = merged_df_2001['RET']
# Perform the regression using statsmodels
model_all_sectors = sm.OLS(y, X_all_sectors).fit()

# Identify the industry with the coefficient value closest to zero
reference_sector = model_all_sectors.params.abs().idxmin()

print(reference_sector)

sector_35.0

# Create dummy variables for the industry sectors
X_all_sectors = pd.get_dummies(merged_df_2001['gsector'], prefix='sector')
y = merged_df_2001['RET']

# Exclude the reference sector's dummy variable from the independent variables
X = X_all_sectors.drop(columns=[reference_sector])

# Add a constant to the independent variables
X = sm.add_constant(X)

# Perform the regression using statsmodels without the reference sector's dummy varia
model_5 = sm.OLS(y, X).fit()

# Print the regression output
print(model_5.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          RET      R-squared:          0.148
Model:                  OLS      Adj. R-squared:       0.144
Method:                 Least Squares      F-statistic:        34.11
Date:                  Sat, 06 May 2023      Prob (F-statistic):  9.67e-62
Time:                  12:35:50      Log-Likelihood:     2933.6
No. Observations:      1973      AIC:                -5845.
Df Residuals:          1962      BIC:                -5784.
Df Model:              10
Covariance Type:       nonrobust
=====
```

	coef	std err	t	P> t	[0.025	0.975]
--	------	---------	---	------	--------	--------

```

-----
const          0.0004      0.004      0.115      0.909      -0.007      0.008
sector_10.0     0.0219      0.007      3.115      0.002      0.008      0.036
sector_15.0     0.0144      0.006      2.214      0.027      0.002      0.027
sector_20.0     0.0037      0.005      0.758      0.448      -0.006      0.013
sector_25.0     0.0183      0.005      3.730      0.000      0.009      0.028
sector_30.0     0.0218      0.007      3.296      0.001      0.009      0.035
sector_40.0     0.0244      0.005      5.333      0.000      0.015      0.033
sector_45.0    -0.0412      0.005     -8.808      0.000     -0.050     -0.032
sector_50.0    -0.0125      0.010     -1.311      0.190     -0.031      0.006
sector_55.0     0.0204      0.008      2.493      0.013      0.004      0.036
sector_60.0     0.0110      0.008      1.348      0.178     -0.005      0.027
=====
Omnibus:                169.744      Durbin-Watson:                2.021
Prob(Omnibus):           0.000      Jarque-Bera (JB):             862.054
Skew:                    0.224      Prob(JB):                     6.42e-188
Kurtosis:                6.207      Cond. No.                     11.5
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

The regression output shows the results of a linear regression model that aims to predict the return (RET) of companies based on their industry sectors. The model uses dummy variables to represent the different industry sectors, and it excludes one reference sector to avoid multicollinearity.

The R-squared value of the model is 0.148, indicating that only 14.8% of the variation in the dependent variable is explained by the independent variables. The adjusted R-squared value is slightly lower, which suggests that the model might be overfitting the data.

Some of the coefficients have p-values higher than 0.05, indicating that they are not statistically significant. In particular, the coefficient for sector_50.0 has a p-value of 0.190, which suggests that it is not a good predictor of the dependent variable.

The coefficient for the reference sector (sector_20.0) is not shown in the output, as it was excluded from the model. The constant term is also included in the model, with a coefficient of 0.0004.

Overall, the model suggests that the industry sectors of companies have a significant but relatively weak relationship with their returns.

▼ 2001- Conclusion

Therefore, the risk exposures explain the most variance in the stock returns with an explanatory power of 33.7%

▼ Great Recession and Financial Crisis

The Great Recession of 2008 was a severe economic downturn that lasted from late 2007 to mid-2009, triggered by a collapse in the housing market and the subprime mortgage industry in the United States. It caused widespread job losses, foreclosures, and a significant decline in economic activity across the globe, leading to a financial crisis that affected the banking sector and financial markets worldwide. The recession had a lasting impact on many economies and societies, and policymakers implemented a range of measures to prevent another such event from occurring.

Merging the three files together

▼ Run OLS regression with the following three main categories

1. **Risk Exposures:** This included systematic risk (market risk), SML (Small Minus Big), which is the size risk, and HML (High minus Low), which is the Value vs Growth risk.
2. **Financial Ratios:** This includes various financial ratios, including but not limited to Liquidity, Leverage, Asset Turnover Ratio, Net and Gross Profit Margin, ROE and ROA.
3. **Industry Indicators:** This indicates which industries had the highest amount of affect on stock returns.

```
# Renaming tic to TICKER in the gsector file
gsector_2008 = gsector_2008.rename(columns={'tic': 'TICKER'})

# Merge the DataFrames based on the 'TICKER' column
merged_df_2008 = pd.merge(gsector_2008, ratios_2008, on='TICKER')
merged_df_2008 = pd.merge(merged_df_2008, ff_2008, on='TICKER')
```

```
merged_df_2008.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2440 entries, 0 to 2439
Data columns (total 38 columns):
#   Column                Non-Null Count  Dtype
---  -
0   gvkey_x                2440 non-null   int64
1   fyear_x                2440 non-null   int64
2   TICKER                 2440 non-null   object
3   gsector                2440 non-null   float64
4   gvkey_y                2440 non-null   int64
5   datadate               2440 non-null   object
6   fyear_y                2440 non-null   int64
7   indfmt                2440 non-null   object
```

```

8  consol      2440 non-null  object
9  popsrc      2440 non-null  object
10 datafmt     2440 non-null  object
11 curcd       2440 non-null  object
12 act         2440 non-null  float64
13 at          2440 non-null  float64
14 che         2440 non-null  float64
15 cogs        2440 non-null  float64
16 dltd        2440 non-null  float64
17 lct         2440 non-null  float64
18 lt          2440 non-null  float64
19 ni          2440 non-null  float64
20 re          2440 non-null  float64
21 sale        2440 non-null  float64
22 costat      2440 non-null  object
23 RET         2440 non-null  float64
24 Net Profit Margin  2440 non-null  float64
25 Gross Profit Margin  2440 non-null  float64
26 Total Debt/Equity  2440 non-null  float64
27 Return on Equity  2440 non-null  float64
28 Liquidity    2440 non-null  float64
29 ROA         2440 non-null  float64
30 Debt/Total Assets  2440 non-null  float64
31 Asset Turnover Ratio  2440 non-null  float64
32 at_log      2440 non-null  float64
33 Unnamed: 0   2440 non-null  int64
34 const       2440 non-null  float64
35 mktrf       2440 non-null  float64
36 smb         2440 non-null  float64
37 hml         2440 non-null  float64
dtypes: float64(25), int64(5), object(8)
memory usage: 743.4+ KB

```

▼ 2008- Regression 1

Regression using financial ratios, risk exposures and industry indicators

```

# General regression code:
X1 = merged_df_2008[['Total Debt/Equity', 'ROA', 'Asset Turnover Ratio']]
X2 = pd.get_dummies(merged_df_2008['gsector'], prefix='sector')
X3 = merged_df_2008[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2, X3], axis=1)

y = merged_df_2008['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

```

```
# list regression output
print(model.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.698
Model:                  OLS      Adj. R-squared:       0.696
Method:                 Least Squares      F-statistic:        350.8
Date:                  Sat, 06 May 2023      Prob (F-statistic):    0.00
Time:                  12:27:42      Log-Likelihood:       3446.3
No. Observations:      2440      AIC:                 -6859.
Df Residuals:          2423      BIC:                 -6760.
Df Model:              16
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	0.0156	0.003	4.883	0.000	0.009
Total Debt/Equity	-0.0001	0.000	-0.328	0.743	-0.001
ROA	0.0512	0.009	5.783	0.000	0.034
Asset Turnover Ratio	-0.0017	0.002	-0.863	0.388	-0.006
sector_10.0	-0.0392	0.005	-7.901	0.000	-0.049
sector_15.0	-0.0044	0.005	-0.861	0.389	-0.014
sector_20.0	0.0019	0.004	0.538	0.591	-0.005
sector_25.0	0.0018	0.004	0.470	0.638	-0.006
sector_30.0	0.0062	0.006	1.074	0.283	-0.005
sector_35.0	-0.0014	0.004	-0.403	0.687	-0.008
sector_40.0	0.0189	0.004	4.744	0.000	0.011
sector_45.0	0.0012	0.003	0.373	0.709	-0.005
sector_50.0	0.0058	0.007	0.856	0.392	-0.007
sector_55.0	0.0155	0.006	2.433	0.015	0.003
sector_60.0	0.0094	0.006	1.531	0.126	-0.003
mktrf	-0.1322	0.002	-65.514	0.000	-0.136
smb	-0.0200	0.001	-15.081	0.000	-0.023
hml	-0.0173	0.001	-13.158	0.000	-0.020

```

=====
Omnibus:              146.830      Durbin-Watson:          1.974
Prob(Omnibus):        0.000      Jarque-Bera (JB):       627.175
Skew:                 0.021      Prob(JB):               6.47e-137
Kurtosis:             5.483      Cond. No.                2.27e+16
=====

```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly
- [2] The smallest eigenvalue is 1.27e-28. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

The OLS regression model examines the relationship between stock returns (RET) and various independent variables, including financial ratios and sector dummies. The model's R-squared value indicates that about 69.8% of the variation in the dependent variable is explained by the model, with an adjusted R-squared of 69.6%. The coefficients of the independent variables show that only ROA, sector_10.0, sector_40.0, sector_55.0, mktrf, smb, and hml have statistically significant impacts on

stock returns. The model may suffer from multicollinearity and singularity issues, indicating a need for further analysis as done below.

▼ 2008- Regression 2

Regression using financial ratios and industry indicators

```
# General regression code:
X1 = merged_df_2008[['Total Debt/Equity', 'ROA', 'Asset Turnover Ratio']]
X2 = pd.get_dummies(merged_df_2008['gsector'], prefix='sector')

X = pd.concat([X1, X2], axis=1)

y = merged_df_2008['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())
```

OLS Regression Results					
=====					
Dep. Variable:	RET	R-squared:	0.130		
Model:	OLS	Adj. R-squared:	0.126		
Method:	Least Squares	F-statistic:	27.95		
Date:	Sat, 06 May 2023	Prob (F-statistic):	1.38e-64		
Time:	12:27:42	Log-Likelihood:	2153.9		
No. Observations:	2440	AIC:	-4280.		
Df Residuals:	2426	BIC:	-4199.		
Df Model:	13				
Covariance Type:	nonrobust				
=====					
	coef	std err	t	P> t	[0.025

const	-0.1292	0.004	-34.013	0.000	-0.137
Total Debt/Equity	8.641e-05	0.001	0.135	0.893	-0.001
ROA	0.1095	0.015	7.379	0.000	0.080
Asset Turnover Ratio	-0.0016	0.003	-0.468	0.640	-0.008
sector_10.0	-0.0624	0.008	-7.503	0.000	-0.079
sector_15.0	-0.0381	0.009	-4.448	0.000	-0.055
sector_20.0	-0.0222	0.006	-3.794	0.000	-0.034
sector_25.0	-0.0351	0.006	-5.648	0.000	-0.047
sector_30.0	0.0321	0.010	3.310	0.001	0.013
sector_35.0	-0.0034	0.006	-0.558	0.577	-0.015
sector_40.0	0.0404	0.007	6.167	0.000	0.028
sector_45.0	-0.0387	0.005	-7.645	0.000	-0.049
sector_50.0	-0.0387	0.011	-3.380	0.001	-0.061
sector_55.0	0.0698	0.011	6.531	0.000	0.049

```

sector_60.0          -0.0329          0.010          -3.228          0.001          -0.053
=====
Omnibus:              146.074          Durbin-Watson:              1.955
Prob(Omnibus):         0.000          Jarque-Bera (JB):              602.311
Skew:                  -0.083          Prob(JB):              1.62e-131
Kurtosis:              5.428          Cond. No.              1.86e+16
=====

```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly
- [2] The smallest eigenvalue is 1.86e-28. This might indicate that there are strong multicollinearity problems or that the design matrix is singular.

This is the output of a multiple linear regression analysis where the dependent variable is RET (return) and 13 independent variables have been used in the model.

The adjusted R-squared value for the model is 0.126, indicating that approximately 13% of the variation in the dependent variable can be explained by the independent variables included in the model. The adjusted R-squared value takes into account the number of independent variables in the model and adjusts the R-squared value accordingly. In this case, the adjusted R-squared value is slightly lower than the R-squared value of 0.130, which is the proportion of the variation in the dependent variable explained by the model.

Based on the output, it appears that Total Debt/Equity and Asset Turnover Ratio are not statistically significant as their p-values are greater than 0.05. The other 11 independent variables, including ROA (return on assets) and the sector variables, appear to be statistically significant in explaining the variation in the dependent variable.

The significantly low R-Squared suggests that most variability in the data was explained by the risk exposures.

▼ 2001- Regression 3

Regression using only financial ratios and risk exposure

```

# General regression code:
X1 = merged_df_2008[['Total Debt/Equity', 'ROA', 'Asset Turnover Ratio']]
X2 = merged_df_2008[['mkttrf', 'smb', 'hml']]

X = pd.concat([X1, X2], axis=1)

y = merged_df_2008['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

```

```
# list regression output
print(model.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.688
Model:                  OLS      Adj. R-squared:     0.687
Method:                 Least Squares      F-statistic:       893.5
Date:                  Sat, 06 May 2023      Prob (F-statistic): 0.00
Time:                  12:27:42      Log-Likelihood:    3404.0
No. Observations:      2440      AIC:               -6794.
Df Residuals:          2433      BIC:               -6753.
Df Model:               6
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	0.0208	0.003	6.271	0.000	0.014
Total Debt/Equity	0.0008	0.000	2.499	0.013	0.000
ROA	0.0452	0.009	5.242	0.000	0.028
Asset Turnover Ratio	-0.0039	0.002	-2.220	0.026	-0.007
mktrf	-0.1348	0.002	-69.398	0.000	-0.139
smb	-0.0208	0.001	-15.912	0.000	-0.023
hml	-0.0151	0.001	-12.209	0.000	-0.018

```

=====
Omnibus:              161.737      Durbin-Watson:       1.964
Prob(Omnibus):         0.000      Jarque-Bera (JB):    745.617
Skew:                  -0.067      Prob(JB):            1.23e-162
Kurtosis:              5.705      Cond. No.             36.6
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is the output of an Ordinary Least Squares (OLS) regression model with a dependent variable 'RET' (which stands for Return) and six independent variables: Total Debt/Equity, ROA, Asset Turnover Ratio, mktrf, smb, and hml. The model has been estimated using 2,440 observations. The model has an R-squared value of 0.688, indicating that the independent variables explain 68.8% of the variation in the dependent variable, with an adjusted R-Squared of 68.7%, indicating that there is no overfitting. All independent variables except Total Debt/Equity are statistically significant at a 5% level of significance.

▼ 2008- Regression 4

Regression using only risk exposure

```
#General regression code:
X = merged_df_2008[['mktrf', 'smb', 'hml']]
y = merged_df_2008['RET']
# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

#list regression output
print(model.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  RET    R-squared:                  0.683
Model:                            OLS    Adj. R-squared:             0.683
Method:                 Least Squares    F-statistic:                 1749.
Date:                  Sat, 06 May 2023    Prob (F-statistic):          0.00
Time:                  12:27:42    Log-Likelihood:             3385.0
No. Observations:          2440    AIC:                        -6762.
Df Residuals:              2436    BIC:                        -6739.
Df Model:                   3
Covariance Type:            nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.0239      0.003       9.171     0.000      0.019      0.029
mktrf         -0.1369      0.002     -71.477     0.000     -0.141     -0.133
smb           -0.0227      0.001     -17.874     0.000     -0.025     -0.020
hml           -0.0143      0.001     -11.768     0.000     -0.017     -0.012
=====
Omnibus:                 161.365    Durbin-Watson:              1.952
Prob(Omnibus):            0.000    Jarque-Bera (JB):           703.512
Skew:                    -0.127    Prob(JB):                   1.72e-153
Kurtosis:                 5.618    Cond. No.                    4.33
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

In order to further understand the impact of risk exposures, the below above model is analyzed.

In this multiple linear regression model, the dependent variable is RET (stock returns) with six independent variables: Total Debt/Equity, ROA (return on assets), Asset Turnover Ratio, mktrf (systematic risk), smb (small minus big firms), and hml (high minus low book-to-market ratio firms).

This previous model showed that all six independent variables were statistically significant in predicting the dependent variable. The R-squared value was 0.688, which means that 68.8% of the variation in the dependent variable was explained by the independent variables.

This model shows a simplified version of the previous model, with only three independent variables: mktrf, smb, and hml. These three variables are also statistically significant in predicting the

dependent variable. The R-squared value is 0.683, which means that 68.3% of the variation in the dependent variable is explained solely by the risk exposures.

▼ 2008- Regression 5

Regression with industry sectors

```
X_all_sectors = pd.get_dummies(merged_df_2008['gsector'], prefix='sector')
y = merged_df_2008['RET']
# Perform the regression using statsmodels
model_all_sectors = sm.OLS(y, X_all_sectors).fit()

# Identify the industry with the coefficient value closest to zero
reference_sector = model_all_sectors.params.abs().idxmin()

print(reference_sector)

sector_55.0

# Create dummy variables for the industry sectors
X_all_sectors = pd.get_dummies(merged_df_2008['gsector'], prefix='sector')
y = merged_df_2008['RET']

# Exclude the reference sector's dummy variable from the independent variables
X = X_all_sectors.drop(columns=[reference_sector])

# Add a constant to the independent variables
X = sm.add_constant(X)

# Perform the regression using statsmodels without the reference sector's dummy varia
model_5 = sm.OLS(y, X).fit()

# Print the regression output
print(model_5.summary())
```

OLS Regression Results

=====					
Dep. Variable:	RET	R-squared:		0.110	
Model:	OLS	Adj. R-squared:		0.107	
Method:	Least Squares	F-statistic:		30.15	
Date:	Sat, 06 May 2023	Prob (F-statistic):		2.70e-55	
Time:	12:37:00	Log-Likelihood:		2126.4	
No. Observations:	2440	AIC:		-4231.	
Df Residuals:	2429	BIC:		-4167.	
Df Model:	10				
Covariance Type:	nonrobust				
=====					
	coef	std err	t	P> t	[0.025 0.975]

```

const          -0.0565    0.011    -4.922    0.000    -0.079    -0.034
sector_10.0     -0.1251    0.014    -8.661    0.000    -0.153    -0.097
sector_15.0     -0.1049    0.015    -7.167    0.000    -0.134    -0.076
sector_20.0     -0.0903    0.013    -7.051    0.000    -0.115    -0.065
sector_25.0     -0.1067    0.013    -8.239    0.000    -0.132    -0.081
sector_30.0     -0.0359    0.015    -2.368    0.018    -0.066    -0.006
sector_35.0     -0.0846    0.013    -6.553    0.000    -0.110    -0.059
sector_40.0     -0.0298    0.012    -2.411    0.016    -0.054    -0.006
sector_45.0     -0.1128    0.012    -9.055    0.000    -0.137    -0.088
sector_50.0     -0.1077    0.017    -6.374    0.000    -0.141    -0.075
sector_60.0     -0.1014    0.016    -6.444    0.000    -0.132    -0.071
=====
Omnibus:                140.013    Durbin-Watson:                1.939
Prob(Omnibus):           0.000    Jarque-Bera (JB):            488.539
Skew:                    -0.182    Prob(JB):                     8.22e-107
Kurtosis:                5.162    Cond. No.                     20.2
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

The regression output shows the results of the OLS regression model that predicts the returns of companies based on their industry sectors. The R-squared value of the model is 0.110, which means that 11% of the variance in the dependent variable (RET) is explained by the independent variables (the dummy variables for industry sectors).

The coefficients for each industry sector are negative, which means that, on average, companies in these sectors have lower returns than the reference sector (which is not included in the model).

The reference sector (sector 55) is not explicitly mentioned in the output, but it can be inferred from the fact that one dummy variable is excluded from the model. The reference sector is the industry sector that has the coefficient value closest to zero.

The coefficients of the different sectors indicate how much the return of a company is affected by the sector it belongs to, compared to the reference sector. For example, companies in sector 10.0, which is the energy sector, have returns that are 0.1251 lower, on average, than the reference sector, which is Utilities. Similarly, companies in Consumer Discretionary sector (25.0) have returns that are 0.1067 lower, on average, than the reference sector.

The intercept coefficient (const) is -0.0565, which means that, on average, a company in the reference sector has a return of -0.0565 when all other independent variables are held constant.

Overall, the results suggest that industry sector is a significant predictor of company returns, with different sectors having varying levels of impact on returns.

▼ 2001- Conclusion

For the Great Recession of 2008, the most explanatory power is held by the risk exposures.

▼ The Covid Shock

The COVID-19 pandemic caused a global stock market crash in 2020, with major indices experiencing significant declines in March. Lockdowns and travel restrictions led to supply chain disruptions and reduced consumer spending, negatively impacting many industries.

▼ Merging the three files together

```
# Renaming tic to TICKER in the gsector file
gsector_2020 = gsector_2020.rename(columns={'tic': 'TICKER'})

# Merge the DataFrames based on the 'TICKER' column
merged_df_2020 = pd.merge(gsector_2020, ratios_2020, on='TICKER')
merged_df_2020 = pd.merge(merged_df_2020, ff_2020, on='TICKER')
```

```
merged_df_2020.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2961 entries, 0 to 2960
Data columns (total 38 columns):
#   Column              Non-Null Count  Dtype
---  -
0   gvkey_x              2961 non-null   int64
1   fyear_x              2961 non-null   int64
2   TICKER               2961 non-null   object
3   gsector              2960 non-null   float64
4   gvkey_y              2961 non-null   int64
5   datadate             2961 non-null   object
6   fyear_y              2961 non-null   int64
7   indfmt              2961 non-null   object
8   consol              2961 non-null   object
9   popsrc              2961 non-null   object
10  datafmt             2961 non-null   object
11  curcd               2961 non-null   object
12  act                 2961 non-null   float64
13  at                  2961 non-null   float64
14  che                 2961 non-null   float64
15  cogs                2961 non-null   float64
16  dltd               2961 non-null   float64
17  lct                 2961 non-null   float64
18  lt                  2961 non-null   float64
19  ni                  2961 non-null   float64
```

```

20 re                2961 non-null    float64
21 sale              2961 non-null    float64
22 costat            2961 non-null    object
23 RET                2961 non-null    float64
24 Net Profit Margin  2961 non-null    float64
25 Gross Profit Margin 2961 non-null    float64
26 Total Debt/Equity   2961 non-null    float64
27 Return on Equity    2961 non-null    float64
28 Liquidity           2961 non-null    float64
29 ROA                2961 non-null    float64
30 Debt/Total Assets   2961 non-null    float64
31 Asset Turnover Ratio 2961 non-null    float64
32 at_log              2961 non-null    float64
33 Unnamed: 0          2961 non-null    int64
34 const              2961 non-null    float64
35 mktrf               2961 non-null    float64
36 smb                 2961 non-null    float64
37 hml                 2961 non-null    float64
dtypes: float64(25), int64(5), object(8)
memory usage: 902.2+ KB

```

▼ Run OLS regression with the following three main categories

1. **Risk Exposures:** This included systematic risk (market risk), SML (Small Minus Big), which is the size risk, and HML (High minus Low), which is the Value vs Growth risk.
2. **Financial Ratios:** This includes various financial ratios, including but not limited to Liquidity, Leverage, Asset Turnover Ratio, Net and Gross Profit Margin, ROE and ROA.
3. **Industry Indicators:** This indicates which industries had the highest amount of affect on stock returns.

▼ 2020- Regression 1

Regression with financial ratios, industry indicators and risk exposure

```

# General regression code:
X1 = merged_df_2020[['Gross Profit Margin', 'Liquidity', 'at_log']]
X2 = pd.get_dummies(merged_df_2020['gsector'], prefix='sector')
X3 = merged_df_2020[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2, X3], axis=1)

y = merged_df_2020['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant

```



```
model = sm.OLS(y, X).fit()
```

```
# list regression output
print(model.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.556
Model:                  OLS      Adj. R-squared:      0.554
Method:                 Least Squares      F-statistic:        217.2
Date:                   Sat, 06 May 2023      Prob (F-statistic):    0.00
Time:                   12:27:42      Log-Likelihood:       2648.2
No. Observations:       2961      AIC:                 -5260.
Df Residuals:           2943      BIC:                 -5153.
Df Model:               17
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	-0.1412	0.100	-1.416	0.157	-0.337
Gross Profit Margin	-0.0001	0.000	-0.362	0.717	-0.001
Liquidity	-0.0001	0.001	-0.125	0.901	-0.002
at_log	0.0016	0.001	1.621	0.105	-0.000
sector_10.0	0.1460	0.100	1.468	0.142	-0.049
sector_15.0	0.1372	0.100	1.379	0.168	-0.058
sector_20.0	0.1429	0.099	1.438	0.150	-0.052
sector_25.0	0.1184	0.099	1.191	0.234	-0.077
sector_30.0	0.1424	0.100	1.429	0.153	-0.053
sector_35.0	0.1662	0.099	1.671	0.095	-0.029
sector_40.0	0.1178	0.099	1.186	0.236	-0.077
sector_45.0	0.1503	0.099	1.512	0.131	-0.045
sector_50.0	0.1294	0.100	1.298	0.194	-0.066
sector_55.0	0.0985	0.100	0.986	0.324	-0.097
sector_60.0	0.0960	0.100	0.964	0.335	-0.099
mktrf	-0.1298	0.003	-45.836	0.000	-0.135
smb	-0.0076	0.002	-3.651	0.000	-0.012
hml	-0.0778	0.003	-27.502	0.000	-0.083

```

=====
Omnibus:                4465.985      Durbin-Watson:          1.964
Prob(Omnibus):           0.000      Jarque-Bera (JB):       5445507.010
Skew:                    8.722      Prob(JB):               0.00
Kurtosis:                212.365      Cond. No.               1.56e+03
=====

```

Notes:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly
- [2] The condition number is large, 1.56e+03. This might indicate that there are strong multicollinearity or other numerical problems.

The multiple linear regression model has an adjusted R-squared value of 0.554, indicating that the model explains around 55% of the variance in the dependent variable. Among the independent variables, only mktrf, smb, and hml have p-values less than 0.05, indicating that they are statistically significant predictors of the dependent variable at a 95% confidence level. The coefficients of these

variables are negative, indicating that they have a negative effect on the stock returns. The other independent variables, including const, Gross Profit Margin, Liquidity, at_log, and sector variables, are not statistically significant at a 95% confidence level.

Here we also see that the as risk increased, including market risk, size risk and distress risk, this negatively impacted the stock returns.

However, the model also has some potential issues with multicollinearity and numerical problems.

▼ 2020- Regression 2

Regression with financial ratios and industry indicators

```
# General regression code:
X1 = merged_df_2020[['Gross Profit Margin', 'Liquidity', 'at_log']]
X2 = pd.get_dummies(merged_df_2020['gsector'], prefix='sector')

X = pd.concat([X1, X2], axis=1)

y = merged_df_2020['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())
```

OLS Regression Results					
=====					
Dep. Variable:	RET	R-squared:	0.124		
Model:	OLS	Adj. R-squared:	0.120		
Method:	Least Squares	F-statistic:	29.83		
Date:	Sat, 06 May 2023	Prob (F-statistic):	8.58e-75		
Time:	12:27:42	Log-Likelihood:	1640.9		
No. Observations:	2961	AIC:	-3252.		
Df Residuals:	2946	BIC:	-3162.		
Df Model:	14				
Covariance Type:	nonrobust				
=====					
	coef	std err	t	P> t	[0.025

const	-0.3420	0.140	-2.446	0.014	-0.616
Gross Profit Margin	0.0007	0.001	1.227	0.220	-0.000
Liquidity	0.0050	0.001	3.902	0.000	0.002
at_log	-0.0020	0.001	-1.541	0.123	-0.005
sector_10.0	0.0764	0.140	0.547	0.585	-0.198
sector_15.0	0.1763	0.140	1.261	0.207	-0.098
sector_20.0	0.1779	0.140	1.275	0.202	-0.096

sector_25.0	0.1317	0.140	0.943	0.346	-0.142
sector_30.0	0.2656	0.140	1.897	0.058	-0.009
sector_35.0	0.2568	0.140	1.840	0.066	-0.017
sector_40.0	0.1799	0.140	1.289	0.197	-0.094
sector_45.0	0.2182	0.140	1.564	0.118	-0.055
sector_50.0	0.2084	0.140	1.489	0.137	-0.066
sector_55.0	0.2536	0.140	1.808	0.071	-0.021
sector_60.0	0.1734	0.140	1.240	0.215	-0.101

Omnibus:	4539.402	Durbin-Watson:	1.929
Prob(Omnibus):	0.000	Jarque-Bera (JB):	5883822.268
Skew:	9.007	Prob(JB):	0.00
Kurtosis:	220.637	Cond. No.	1.55e+03

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly
 [2] The condition number is large, 1.55e+03. This might indicate that there are strong multicollinearity or other numerical problems.

This is an OLS regression analysis of the dependent variable RET (stock returns) and 14 independent variables. The adjusted R-squared value is 0.120, which means that the model explains 12% of the variance in the dependent variable after adjusting for the number of independent variables. However, only the independent variables Liquidity and sector_30.0 are significant at a 95% confidence level ($P < 0.05$), whereas the other independent variables are not significant. There might be some numerical problems or strong multicollinearity in the data, indicated by the large condition number of 1.55e+03.

This significantly low explanatory power is a result of removing market, size and distress risk from the regression.

▼ 2020- Regression 3

Regression with financial ratios and risk exposure

```
# General regression code:
X1 = merged_df_2020[['Gross Profit Margin', 'Liquidity', 'at_log']]
X2 = merged_df_2020[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2], axis=1)

y = merged_df_2020['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
```

```
# list regression output
print(model.summary())
```

```

=====
                        OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.542
Model:                  OLS      Adj. R-squared:       0.541
Method:                 Least Squares      F-statistic:       583.2
Date:                  Sat, 06 May 2023      Prob (F-statistic): 0.00
Time:                  12:27:43      Log-Likelihood:    2601.5
No. Observations:      2961      AIC:               -5189.
Df Residuals:          2954      BIC:               -5147.
Df Model:              6
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	-0.0036	0.009	-0.386	0.700	-0.022
Gross Profit Margin	-0.0004	0.000	-1.003	0.316	-0.001
Liquidity	0.0013	0.001	1.393	0.164	-0.001
at_log	0.0002	0.001	0.236	0.814	-0.002
mktrf	-0.1251	0.003	-47.042	0.000	-0.130
smb	-0.0063	0.002	-3.046	0.002	-0.010
hml	-0.0842	0.003	-33.077	0.000	-0.089

```

=====
Omnibus:              4454.761      Durbin-Watson:          1.953
Prob(Omnibus):        0.000      Jarque-Bera (JB):      5375759.179
Skew:                 8.680      Prob(JB):              0.00
Kurtosis:             211.017      Cond. No.              42.7
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is a linear regression model with a dependent variable RET (stock returns) and six independent variables: Gross Profit Margin, Liquidity, at_log, mktrf, smb, and hml. The model has an R-squared of 0.542, indicating that 54.2% of the variability in the dependent variable is explained by the independent variables. Only the variables mktrf, smb, and hml have statistically significant coefficients at the 5% level. The constant term is not statistically significant.

As risk exposures were put back into the regression, the model's explanatory power and improved significantly.

▼ 2020- Regression 4

Regression with only risk exposure

```
#General regression code:
X = merged_df_2020[['mktrf', 'smb', 'hml']]
y = merged_df_2020['RET']
# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

#list regression output
print(model.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  RET    R-squared:                  0.542
Model:                            OLS    Adj. R-squared:             0.541
Method:                 Least Squares    F-statistic:                 1165.
Date:                  Sat, 06 May 2023    Prob (F-statistic):          0.00
Time:                  12:27:43    Log-Likelihood:             2599.8
No. Observations:                2961    AIC:                        -5192.
Df Residuals:                    2957    BIC:                        -5168.
Df Model:                          3
Covariance Type:                nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          0.0012      0.004      0.318      0.751      -0.006      0.008
mktrf         -0.1252      0.003     -47.482      0.000      -0.130     -0.120
smb           -0.0059      0.002      -2.999      0.003      -0.010     -0.002
hml           -0.0852      0.002     -35.061      0.000      -0.090     -0.080
=====
Omnibus:                 4439.223    Durbin-Watson:              1.952
Prob(Omnibus):             0.000    Jarque-Bera (JB):           5268487.010
Skew:                      8.622    Prob(JB):                   0.00
Kurtosis:                 208.926    Cond. No.                   4.13
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

The OLS regression model has an R-squared of 0.542, indicating that the model explains 54.2% of the variability in the dependent variable. The coefficients for Gross Profit Margin and Liquidity are not statistically significant at a 5% level. The final model includes the market factor (mktrf), size factor (smb), and value factor (hml), which are all statistically significant at a 5% level. The adjusted R-squared is 0.541, indicating that the model has a good fit. The model is also free from multicollinearity issues as evidenced by the low condition number.

It is also important to note the inverse relationship between risk exposures and stock returns.

▼ 2020- Regression 5

Regression with only industry indicators

```
X_all_sectors = pd.get_dummies(merged_df_2020['gsector'], prefix='sector')
y = merged_df_2020['RET']
# Perform the regression using statsmodels
model_all_sectors = sm.OLS(y, X_all_sectors).fit()

# Identify the industry with the coefficient value closest to zero
reference_sector = model_all_sectors.params.abs().idxmin()

print(reference_sector)

sector_35.0

# Create dummy variables for the industry sectors
X_all_sectors = pd.get_dummies(merged_df_2020['gsector'], prefix='sector')
y = merged_df_2020['RET']

# Exclude the reference sector's dummy variable from the independent variables
X = X_all_sectors.drop(columns=[reference_sector])

# Add a constant to the independent variables
X = sm.add_constant(X)

# Perform the regression using statsmodels without the reference sector's dummy varia
model_5 = sm.OLS(y, X).fit()

# Print the regression output
print(model_5.summary())
```

OLS Regression Results

=====						
Dep. Variable:		RET	R-squared:		0.116	
Model:		OLS	Adj. R-squared:		0.113	
Method:		Least Squares	F-statistic:		38.64	
Date:		Sat, 06 May 2023	Prob (F-statistic):		5.20e-72	
Time:		12:50:31	Log-Likelihood:		1626.8	
No. Observations:		2961	AIC:		-3232.	
Df Residuals:		2950	BIC:		-3166.	
Df Model:		10				
Covariance Type:		nonrobust				
=====						
	coef	std err	t	P> t	[0.025	0.975]

const	-0.0807	0.007	-11.584	0.000	-0.094	-0.067
sector_10.0	-0.1890	0.012	-15.490	0.000	-0.213	-0.165
sector_15.0	-0.0876	0.013	-6.819	0.000	-0.113	-0.062
sector_20.0	-0.0870	0.010	-9.002	0.000	-0.106	-0.068
sector_25.0	-0.1351	0.010	-12.949	0.000	-0.156	-0.115
sector_30.0	-0.0010	0.015	-0.069	0.945	-0.030	0.028
sector_40.0	-0.0899	0.009	-9.865	0.000	-0.108	-0.072

```

sector_45.0    -0.0424    0.010    -4.238    0.000    -0.062    -0.023
sector_50.0    -0.0590    0.015    -4.029    0.000    -0.088    -0.030
sector_55.0    -0.0206    0.017    -1.185    0.236    -0.055    0.013
sector_60.0    -0.0928    0.013    -7.280    0.000    -0.118    -0.068
=====
Omnibus:                4500.352    Durbin-Watson:                1.935
Prob(Omnibus):           0.000    Jarque-Bera (JB):            5598648.604
Skew:                    8.858    Prob(JB):                     0.00
Kurtosis:                215.286    Cond. No.                     10.4
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is a linear regression model with the dependent variable RET (return) and ten independent variables, which are dummy variables for industry sectors (excluding the reference sector with the coefficient closest to zero). The model has an R-squared value of 0.116, which means that 11.6% of the variation in the dependent variable can be explained by the independent variables.

Here, a one-unit increase in sector_10.0 (Energy Sector) is associated with a 0.1890 decrease in RET (stock return), holding all other independent variables constant.

The reference sector is sector_30.0, which is the Consumer Staples Sector, and its coefficient is not statistically significant with a p-value of 0.945, indicating that there is no significant difference in return between sector_30.0 and the reference sector.

The coefficients of the other independent variables are all statistically significant with p-values less than 0.05.

▼ 2020- Conclusion

As in the models before for the previous 3 stock market crashes, risk exposures explain the most variability in returns for the months leading up to the Covid Crash in 2020.

▼ The end of Easy Money

The Easy Money stock market crash of 2022 occurred due to the Federal Reserve's decision to raise interest rates, leading to a significant drop in stock prices. The crash resulted in significant losses for investors and sparked concerns about the stability of the financial system.

▼ Merging the three files together

```
# Renaming tic to TICKER in the gsector file
gsector_2022 = gsector_2022.rename(columns={'tic': 'TICKER'})

# Merge the DataFrames based on the 'TICKER' column
merged_df_2022 = pd.merge(gsector_2022, ratios_2022, on='TICKER')
merged_df_2022 = pd.merge(merged_df_2022, ff_2022, on='TICKER')

merged_df_2022.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 3026 entries, 0 to 3025
Data columns (total 38 columns):
#   Column                                Non-Null Count  Dtype
---  -
0   gvkey_x                               3026 non-null   int64
1   fyear_x                               3026 non-null   int64
2   TICKER                               3026 non-null   object
3   gsector                              3025 non-null   float64
4   gvkey_y                               3026 non-null   int64
5   datadate                             3026 non-null   object
6   fyear_y                               3026 non-null   int64
7   indfmt                                3026 non-null   object
8   consol                               3026 non-null   object
9   popsrc                                3026 non-null   object
10  datafmt                                3026 non-null   object
11  curcd                                 3026 non-null   object
12  act                                   3026 non-null   float64
13  at                                   3026 non-null   float64
14  che                                   3026 non-null   float64
15  cogs                                  3026 non-null   float64
16  dltd                                  3026 non-null   float64
17  lct                                   3026 non-null   float64
18  lt                                    3026 non-null   float64
19  ni                                    3026 non-null   float64
20  re                                    3026 non-null   float64
21  sale                                  3026 non-null   float64
22  costat                                3026 non-null   object
23  RET                                   3026 non-null   float64
24  Net Profit Margin                    3026 non-null   float64
25  Gross Profit Margin                  3026 non-null   float64
26  Total Debt/Equity                    3026 non-null   float64
27  Return on Equity                     3026 non-null   float64
28  Liquidity                             3026 non-null   float64
29  ROA                                   3026 non-null   float64
30  Debt/Total Assets                    3026 non-null   float64
31  Asset Turnover Ratio                 3026 non-null   float64
32  at_log                               3026 non-null   float64
33  Unnamed: 0                           3026 non-null   int64
34  const                                3026 non-null   float64
```



```

35  mktrf          3026 non-null    float64
36  smb            3026 non-null    float64
37  hml            3026 non-null    float64
dtypes: float64(25), int64(5), object(8)
memory usage: 922.0+ KB

```

▼ Run OLS regression with the following three main categories

1. **Risk Exposures:** This included systematic risk (market risk), SML (Small Minus Big), which is the size risk, and HML (High minus Low), which is the Value vs Growth risk.
2. **Financial Ratios:** This includes various financial ratios, including but not limited to Liquidity, Leverage, Asset Turnover Ratio, Net and Gross Profit Margin, ROE and ROA.
3. **Industry Indicators:** This indicates which industries had the highest amount of affect on stock returns.

▼ 2022- Regression 1

Regression with financial ratios, industry indicators and risk exposures

```

# General regression code:
X1 = merged_df_2022[['Gross Profit Margin', 'Liquidity', 'at_log']]
X2 = pd.get_dummies(merged_df_2022['gsector'], prefix='sector')
X3 = merged_df_2022[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2, X3], axis=1)

y = merged_df_2022['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())

```

OLS Regression Results

```

=====
Dep. Variable:          RET    R-squared:                0.231
Model:                  OLS    Adj. R-squared:         0.227
Method:                 Least Squares    F-statistic:          53.20
Date:                   Sat, 06 May 2023    Prob (F-statistic):    1.67e-157
Time:                   12:27:43    Log-Likelihood:        3866.7
No. Observations:       3026    AIC:                   -7697.
Df Residuals:           3008    BIC:                   -7589.
Df Model:                17

```

Covariance Type: nonrobust					
	coef	std err	t	P> t	[0.025
const	0.0311	0.068	0.458	0.647	-0.102
Gross Profit Margin	-0.0004	0.000	-1.937	0.053	-0.001
Liquidity	0.0013	0.000	3.065	0.002	0.000
at_log	0.0017	0.001	2.509	0.012	0.000
sector_10.0	-0.0252	0.068	-0.371	0.710	-0.158
sector_15.0	-0.0752	0.068	-1.109	0.267	-0.208
sector_20.0	-0.0455	0.068	-0.671	0.502	-0.178
sector_25.0	-0.0468	0.068	-0.690	0.490	-0.180
sector_30.0	-0.0391	0.068	-0.576	0.565	-0.172
sector_35.0	-0.0534	0.068	-0.788	0.431	-0.186
sector_40.0	-0.0575	0.068	-0.849	0.396	-0.190
sector_45.0	-0.0494	0.068	-0.729	0.466	-0.182
sector_50.0	-0.0655	0.068	-0.964	0.335	-0.199
sector_55.0	-0.0404	0.068	-0.594	0.553	-0.174
sector_60.0	-0.0705	0.068	-1.038	0.299	-0.204
mktrf	-0.0508	0.002	-21.899	0.000	-0.055
smb	-0.0139	0.001	-14.183	0.000	-0.016
hml	0.0299	0.002	13.701	0.000	0.026
Omnibus:	505.374	Durbin-Watson:		1.984	
Prob(Omnibus):	0.000	Jarque-Bera (JB):		7643.782	
Skew:	0.299	Prob(JB):		0.00	
Kurtosis:	10.763	Cond. No.		1.62e+03	

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly
 [2] The condition number is large, 1.62e+03. This might indicate that there are strong multicollinearity or other numerical problems.

The OLS regression model shows that the R-squared value is 0.231, indicating that the model explains only 23.1% of the variation in the dependent variable, with an adjusted R-Squared of 22.7%.

The regression coefficients for Gross Profit Margin, sector_10.0, sector_15.0, sector_20.0, sector_25.0, sector_30.0, sector_35.0, sector_40.0, sector_45.0, sector_50.0, sector_55.0, and sector_60.0 are not statistically significant at the 5% level. The regression coefficients for Liquidity, at_log, mktrf, smb, and hml are statistically significant at the 5% level.

The model's goodness of fit can be improved, as indicated by the Adjusted R-squared value of 0.227. The coefficients of smb and hml are negative and positive, respectively, suggesting that a higher SMB (size factor) and HML (value factor) are associated with lower and higher stock market returns, respectively.

The model has some potential issues with multicollinearity, as indicated by the large condition number.

▼ 2022- Regression 2

Regression with only financial ratios and industry indicators.

```
# General regression code:
X1 = merged_df_2022[['Gross Profit Margin', 'Liquidity', 'at_log']]
X2 = pd.get_dummies(merged_df_2022['gsector'], prefix='sector')

X = pd.concat([X1, X2], axis=1)

y = merged_df_2022['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

# list regression output
print(model.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.058
Model:                  OLS      Adj. R-squared:       0.054
Method:                 Least Squares      F-statistic:        13.34
Date:                  Sat, 06 May 2023      Prob (F-statistic):  3.06e-31
Time:                  12:27:43      Log-Likelihood:     3560.0
No. Observations:      3026      AIC:                -7090.
Df Residuals:          3011      BIC:                -7000.
Df Model:               14
Covariance Type:       nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	0.0067	0.075	0.090	0.929	-0.140
Gross Profit Margin	0.0003	0.000	1.439	0.150	-0.000
Liquidity	0.0005	0.000	1.071	0.284	-0.000
at_log	0.0028	0.001	3.910	0.000	0.001
sector_10.0	-0.0536	0.075	-0.715	0.475	-0.201
sector_15.0	-0.1057	0.075	-1.409	0.159	-0.253
sector_20.0	-0.0813	0.075	-1.086	0.278	-0.228
sector_25.0	-0.0940	0.075	-1.255	0.210	-0.241
sector_30.0	-0.0561	0.075	-0.747	0.455	-0.203
sector_35.0	-0.1003	0.075	-1.340	0.180	-0.247
sector_40.0	-0.0741	0.075	-0.990	0.322	-0.221
sector_45.0	-0.0995	0.075	-1.328	0.184	-0.246
sector_50.0	-0.1013	0.075	-1.349	0.177	-0.249
sector_55.0	-0.0490	0.075	-0.651	0.515	-0.197
sector_60.0	-0.0985	0.075	-1.313	0.189	-0.246

```

=====
Omnibus:                427.615      Durbin-Watson:          1.979
Prob(Omnibus):           0.000      Jarque-Bera (JB):       5998.136

```

Skew:	0.007	Prob(JB):	0.00
Kurtosis:	9.897	Cond. No.	1.61e+03
=====			

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly
 [2] The condition number is large, 1.61e+03. This might indicate that there are strong multicollinearity or other numerical problems.

The R-squared value of the model is 0.058, indicating that only 5.8% of the variation in the dependent variable is explained by the independent variables. The Adjusted R-squared value is slightly lower at 0.054, suggesting that the model's goodness of fit could be improved.

The coefficients of the independent variables are mostly negative, indicating that all sectors and risk exposures, except for sml, lead to lower stock market returns. However, the p-values of most of these variables are greater than 0.05, suggesting that they are not statistically significant predictors of stock market returns.

The p-value of at_log is less than 0.05, indicating that it is a statistically significant predictor of stock market returns. This suggests that as a company's assets grow, its stock market returns also increase.

The p-values of the sector indicators are mixed, with some being statistically significant predictors of stock market returns (e.g., sector_15.0, which is Materials) and others not (e.g., sector_10.0, which is Energy).

The model's condition number is large, indicating the possible presence of strong multicollinearity or other numerical problems.

▼ 2022- Regression 3

Regression with financial ratios and risk exposures

```
# General regression code:
X1 = merged_df_2022[['Gross Profit Margin', 'Liquidity', 'at_log']]
X2 = merged_df_2022[['mktrf', 'smb', 'hml']]

X = pd.concat([X1, X2], axis=1)

y = merged_df_2022['RET']

# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()
```

```
# list regression output
print(model.summary())
```

```

OLS Regression Results
=====
Dep. Variable:          RET      R-squared:          0.211
Model:                  OLS      Adj. R-squared:       0.209
Method:                 Least Squares      F-statistic:         134.2
Date:                   Sat, 06 May 2023    Prob (F-statistic):   4.77e-151
Time:                   12:27:43      Log-Likelihood:       3826.7
No. Observations:       3026      AIC:                  -7639.
Df Residuals:           3019      BIC:                  -7597.
Df Model:                6
Covariance Type:        nonrobust
=====

```

	coef	std err	t	P> t	[0.025
const	-0.0188	0.006	-3.069	0.002	-0.031
Gross Profit Margin	-0.0004	0.000	-1.943	0.052	-0.001
Liquidity	0.0013	0.000	3.062	0.002	0.000
at_log	0.0011	0.001	1.722	0.085	-0.000
mktrf	-0.0495	0.002	-22.249	0.000	-0.054
smb	-0.0135	0.001	-13.889	0.000	-0.015
hml	0.0322	0.002	16.911	0.000	0.028

```

=====
Omnibus:                488.542      Durbin-Watson:         1.971
Prob(Omnibus):           0.000      Jarque-Bera (JB):       6765.956
Skew:                    0.303      Prob(JB):               0.00
Kurtosis:                10.300      Cond. No.               42.7
=====

```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

The results indicate that the model has an R-squared value of 0.211, which implies that approximately 21.1% of the variance in the dependent variable can be explained by the independent variables. The F-statistic of 134.2 is statistically significant with a p-value of 4.77e-151. The results also indicate that some of the independent variables are statistically significant, while others are not.

Among the statistically significant variables, mktrf, smb, and hml are significant at a 95% level of significance. This implies that these variables have a strong impact on the dependent variable, RET. Specifically, mktrf has a negative coefficient of -0.0495, which means that an increase in the market risk premium will lead to a decrease in the firm's return on equity.

Similarly, smb has a negative coefficient of -0.0135, while hml has a positive coefficient of 0.0322, indicating that an increase in the size and value factors will lead to a decrease and increase, respectively, in the firm's returns.

▼ 2022- Regression 4

Regression with only the risk exposures

```
#General regression code:
X = merged_df_2022[['mktrf', 'smb', 'hml']]
y = merged_df_2022['RET']
# Use statsmodels
X = sm.add_constant(X) # adding a constant
model = sm.OLS(y, X).fit()

#list regression output
print(model.summary())
```

```

                                OLS Regression Results
=====
Dep. Variable:                  RET    R-squared:                  0.207
Model:                            OLS    Adj. R-squared:              0.206
Method:                 Least Squares    F-statistic:                 262.3
Date:                  Sat, 06 May 2023    Prob (F-statistic):          2.75e-151
Time:                  12:27:44    Log-Likelihood:              3819.1
No. Observations:          3026    AIC:                         -7630.
Df Residuals:              3022    BIC:                         -7606.
Df Model:                   3
Covariance Type:            nonrobust
=====
               coef      std err          t      P>|t|      [0.025      0.975]
-----
const          -0.0070      0.003      -2.625      0.009      -0.012      -0.002
mktrf          -0.0491      0.002     -22.090      0.000      -0.053      -0.045
smb            -0.0130      0.001     -14.784      0.000      -0.015      -0.011
hml             0.0308      0.002      17.179      0.000       0.027       0.034
=====
Omnibus:                 488.178    Durbin-Watson:              1.981
Prob(Omnibus):             0.000    Jarque-Bera (JB):           6859.814
Skew:                      0.294    Prob(JB):                     0.00
Kurtosis:                  10.353    Cond. No.                     5.21
=====
```

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

The R-squared value of the model is 0.207, which indicates that the independent variables explain approximately 21% of the variation in the dependent variable. The adjusted R-squared value is 0.206, which accounts for the degrees of freedom in the model.

The coefficients of the independent variables show the effect of each variable on the dependent variable, holding other variables constant. The constant is -0.0070, indicating that the expected value of the dependent variable when all independent variables are equal to zero is -0.0070.

The coefficients of "mktrf", "smb", and "hml" are -0.0491, -0.0130, and 0.0308, respectively. These coefficients suggest that "mktrf" and "smb" have a negative effect on the dependent variable, while "hml" has a positive effect. All three coefficients are statistically significant with p-values less than 0.05.

▼ 2022- Regression 5

Regression with only the industry indicators

```
X_all_sectors = pd.get_dummies(merged_df_2022['gsector'], prefix='sector')
y = merged_df_2022['RET']
# Perform the regression using statsmodels
model_all_sectors = sm.OLS(y, X_all_sectors).fit()

# Identify the industry with the coefficient value closest to zero
reference_sector = model_all_sectors.params.abs().idxmin()

print(reference_sector)

sector_55.0

# Create dummy variables for the industry sectors
X_all_sectors = pd.get_dummies(merged_df_2022['gsector'], prefix='sector')
y = merged_df_2022['RET']

# Exclude the reference sector's dummy variable from the independent variables
X = X_all_sectors.drop(columns=[reference_sector])

# Add a constant to the independent variables
X = sm.add_constant(X)

# Perform the regression using statsmodels without the reference sector's dummy variable
model_5 = sm.OLS(y, X).fit()

# Print the regression output
print(model_5.summary())
```

OLS Regression Results

```
=====
Dep. Variable:          RET      R-squared:                0.053
Model:                  OLS      Adj. R-squared:           0.049
Method:                 Least Squares      F-statistic:             16.71
Date:                  Sat, 06 May 2023     Prob (F-statistic):       8.51e-30
Time:                  12:49:18      Log-Likelihood:          3550.5
No. Observations:      3026      AIC:                     -7079.
Df Residuals:          3015      BIC:                     -7013.
Df Model:              10
```

Covariance Type:		nonrobust				
	coef	std err	t	P> t	[0.025	0.975]
const	-0.0157	0.008	-1.908	0.057	-0.032	0.000
sector_10.0	-0.0095	0.010	-0.958	0.338	-0.029	0.010
sector_15.0	-0.0599	0.010	-5.957	0.000	-0.080	-0.040
sector_20.0	-0.0371	0.009	-4.128	0.000	-0.055	-0.019
sector_25.0	-0.0495	0.009	-5.392	0.000	-0.068	-0.032
sector_30.0	-0.0111	0.011	-1.058	0.290	-0.032	0.010
sector_35.0	-0.0589	0.009	-6.582	0.000	-0.076	-0.041
sector_40.0	-0.0261	0.009	-2.960	0.003	-0.043	-0.009
sector_45.0	-0.0563	0.009	-6.192	0.000	-0.074	-0.038
sector_50.0	-0.0557	0.011	-5.267	0.000	-0.077	-0.035
sector_60.0	-0.0528	0.010	-5.221	0.000	-0.073	-0.033
Omnibus:		422.698	Durbin-Watson:			1.972
Prob(Omnibus):		0.000	Jarque-Bera (JB):			5685.662
Skew:		-0.075	Prob(JB):			0.00
Kurtosis:		9.714	Cond. No.			21.5

Notes:

[1] Standard Errors assume that the covariance matrix of the errors is correctly

This is a regression analysis for the year 2022 using the Ordinary Least Squares (OLS) method. The dependent variable is the 'RET' column, and the independent variables are the dummy variables for the 'gsector' column of the 'merged_df_2022' dataset.

The regression output shows that the R-squared value is 0.053, which means that the model explains only 5.3% of the variance in the dependent variable.

The coefficient values for the different industry sectors indicate the impact of each sector on the dependent variable. The 'sector_15.0' industry has the most significant impact with a coefficient value of -0.0599, which means that a one-unit increase in this sector's dummy variable decreases the dependent variable by 0.0599 units, holding all other variables constant. The reference sector, 'sector_10.0', has a coefficient value of -0.0095, which is not statistically significant.

The model's overall fit can be improved as the adjusted R-squared value is only 0.049.

Overall, this regression analysis suggests that the industry sector has a statistically significant impact on the dependent variable, but the model's fit is not strong enough to make accurate predictions.

▼ 2022- Conclusion

For the End of Easy Money Stock Market Crash, the most variability in the stock returns are explained by the risk exposures

▼ Links and References

- 1. [https://en.wikipedia.org/wiki/ Global_Industry_Classification_Standard](https://en.wikipedia.org/wiki/Global_Industry_Classification_Standard)