Cash Ratio Analysis Notebook

Import Necessary Libraries

In [1]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
sns.set()
```

Read the Excel File into the Jupyter Notebook

The excel file has the following variables:

Variable Name	Variable Description
ID	Firm Identification Code
year	Financial Year of Data
TA	Total Assets
SALES_USD	Net Sales in U.S. Dollars
MKT_EQUITY	Market Value of Common Equity
ST_DEBT	Short Term Debt
LT_DEBT	Long Term Debt
NPPE	Net Property, Plant and Equipment
INTEREST	Interest Expense
EBIT	Earnings Before Interest and Tax
EBITDA	Earnings Before Interest, Tax, Depreciation and Amortisation
Cash	Cash in Balance Sheet
TA_USD	Total Assets in U.S. Dollars
NATION	Nation Code
COUNTRY	Country Name

We read the file using read_excel()

The location of the file is: C:/Users/User/Desktop/

And the name of the file is: international_leverage.xlsx

In [2]:
```
df = pd.read_excel('international_leverage_2023.xlsx', sheet_name='Sheet1')
```

In [3]:
```
# Check the number of rows and columns
df.shape
```

Out[3]:
```
(113285, 17)
```

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

Out[4]:

	ws_num	year	TA	SALES_USD	MKT_EQUITY	BOOK_EQUITY	ST_DEBT	LT_DEBT	NPPE
0	C036AAB00	2009	117.976	35.002	33.991	40.024	0.599	66.559	78.924
1	C036AAB00	2010	38.070	12.213	72.877	-25.373	0.624	59.028	7.547
2	C036AAB00	2011	36.598	15.091	41.710	-35.724	14.907	50.224	6.660
3	C036AAB00	2012	10.703	38.911	1.182	-24.373	0.083	31.215	0.681
4	C036ABF00	2007	934.705	108.515	449.345	403.748	21.303	226.760	697.729

In [5]:
```
df
```

Out[5]:

	ws_num	year	TA	SALES_USD	MKT_EQUITY	BOOK_EQUITY	ST_DEBT	LT_DEBT	N
0	C036AAB00	2009	117.976	35.002	33.991	40.024	0.599	66.559	78
1	C036AAB00	2010	38.070	12.213	72.877	-25.373	0.624	59.028	7
2	C036AAB00	2011	36.598	15.091	41.710	-35.724	14.907	50.224	6
3	C036AAB00	2012	10.703	38.911	1.182	-24.373	0.083	31.215	0
4	C036ABF00	2007	934.705	108.515	449.345	403.748	21.303	226.760	697
...	...	...	...	...	...	...	...	...	
113280	C82699850	2013	255.161	461.951	852.480	148.526	0.000	0.000	19
113281	C82699850	2014	254.385	428.367	912.273	151.499	0.000	0.000	20
113282	C82699850	2015	267.090	435.811	766.491	153.450	0.000	0.000	23
113283	C82699850	2016	294.319	409.292	883.209	165.077	0.000	0.000	20
113284	C82699850	2017	307.890	478.271	980.086	166.745	0.000	0.000	27

113285 rows × 17 columns

Data Pre-processing

For our analysis, we will need the following variables.

So we drop rows with NaN values for: EBIT, MKT_EQUITY, BOOK_EQUITY,TA,SALES_USD,INTEREST.

We use the dropna method to delete the rows with missing values.

In [6]:
```
df1=df.dropna()
```

In [7]:
```
df1.shape
```

Out[7]:
```
(95755, 17)
```

In [8]:
```
# We should use dropna() on a subset of columns which includes the variables we will u
```

In [9]:
```
df1=df.dropna(subset=['EBIT','EBITDA','MKT_EQUITY', 'BOOK_EQUITY','TA','TA_USD','NPPE'
```

In [10]:
```
df1.shape
```

Out[10]:
```
(96947, 17)
```

In [11]:
```
df2=df1.drop_duplicates()
```

In [12]:
```
# Check the number of rows and columns
# 6 rows were deleted.
df2.shape
```

Out[12]:
```
(96947, 17)
```

In [13]:
```
# Change the name of the year variable from 'year' to 'Year'
df2=df2.rename(columns = {'year':'Year'})
df2
```

Out[13]:

	ws_num	Year	TA	SALES_USD	MKT_EQUITY	BOOK_EQUITY	ST_DEBT	LT_DEBT	N
0	C036AAB00	2009	117.976	35.002	33.991	40.024	0.599	66.559	78
1	C036AAB00	2010	38.070	12.213	72.877	-25.373	0.624	59.028	7
2	C036AAB00	2011	36.598	15.091	41.710	-35.724	14.907	50.224	6
3	C036AAB00	2012	10.703	38.911	1.182	-24.373	0.083	31.215	0
4	C036ABF00	2007	934.705	108.515	449.345	403.748	21.303	226.760	697
...	...	...	...	...	...	...	...	...	
113280	C82699850	2013	255.161	461.951	852.480	148.526	0.000	0.000	19
113281	C82699850	2014	254.385	428.367	912.273	151.499	0.000	0.000	20
113282	C82699850	2015	267.090	435.811	766.491	153.450	0.000	0.000	23
113283	C82699850	2016	294.319	409.292	883.209	165.077	0.000	0.000	20
113284	C82699850	2017	307.890	478.271	980.086	166.745	0.000	0.000	27

96947 rows × 17 columns

In [14]:
```
# Set display format option to show three digits after the decimal point
pd.set_option('display.float_format', '{:.2f}'.format)

# Produce descriptive statistics (Transpose (the .T at the end) so the results are mor
df2.describe().T
```

Out[14]:

	count	mean	std	min	25%	50%	75%	max
Year	96947.00	2014.49	4.60	2007.00	2010.00	2015.00	2019.00	2022.00
TA	96947.00	163055.33	1250864.65	5.07	939.77	9049.64	44343.07	71461131.00
SALES_USD	96947.00	1731.15	9164.64	10.00	66.84	207.95	765.79	476914.94
MKT_EQUITY	96947.00	75136.90	455703.10	0.04	612.27	4208.74	20772.99	30622275.18
BOOK_EQUITY	96947.00	56079.54	344353.25	-552947.00	394.70	3911.00	20684.21	26245969.00
ST_DEBT	96054.00	19739.55	278141.34	0.00	7.55	370.82	3213.26	19748395.00
LT_DEBT	96482.00	31931.87	281304.45	-20398.00	4.92	312.00	3191.92	15308519.00
NPPE	96947.00	47294.90	322441.91	0.00	78.71	1625.31	11156.28	12775052.00
INTEREST	96947.00	721.39	9203.35	0.00	1.83	18.06	115.08	958000.00
EBIT	96947.00	7204.61	58343.36	-784440.00	8.67	327.11	2139.10	5977706.00
EBITDA	96947.00	12681.42	97086.12	-446328.00	27.75	573.92	3395.77	6803901.00
CASH	96947.00	25956.75	519448.46	0.00	109.90	1528.00	6954.85	71259671.00
TA_USD	96947.00	2834.52	17253.70	10.02	89.15	275.68	1010.47	1161546.63
NET_INCOME	96944.00	4020.26	41589.33	-1740738.00	2.68	175.42	1250.15	4957716.00
NATION	96947.00	410.98	204.42	36.00	344.00	392.00	392.00	826.00

In [15]:
```
df2.describe().T
```

Out[15]:

	count	mean	std	min	25%	50%	75%	max
Year	96947.00	2014.49	4.60	2007.00	2010.00	2015.00	2019.00	2022.00
TA	96947.00	163055.33	1250864.65	5.07	939.77	9049.64	44343.07	71461131.00
SALES_USD	96947.00	1731.15	9164.64	10.00	66.84	207.95	765.79	476914.94
MKT_EQUITY	96947.00	75136.90	455703.10	0.04	612.27	4208.74	20772.99	30622275.18
BOOK_EQUITY	96947.00	56079.54	344353.25	-552947.00	394.70	3911.00	20684.21	26245969.00
ST_DEBT	96054.00	19739.55	278141.34	0.00	7.55	370.82	3213.26	19748395.00
LT_DEBT	96482.00	31931.87	281304.45	-20398.00	4.92	312.00	3191.92	15308519.00
NPPE	96947.00	47294.90	322441.91	0.00	78.71	1625.31	11156.28	12775052.00
INTEREST	96947.00	721.39	9203.35	0.00	1.83	18.06	115.08	958000.00
EBIT	96947.00	7204.61	58343.36	-784440.00	8.67	327.11	2139.10	5977706.00
EBITDA	96947.00	12681.42	97086.12	-446328.00	27.75	573.92	3395.77	6803901.00
CASH	96947.00	25956.75	519448.46	0.00	109.90	1528.00	6954.85	71259671.00
TA_USD	96947.00	2834.52	17253.70	10.02	89.15	275.68	1010.47	1161546.63
NET_INCOME	96944.00	4020.26	41589.33	-1740738.00	2.68	175.42	1250.15	4957716.00
NATION	96947.00	410.98	204.42	36.00	344.00	392.00	392.00	826.00

In [16]:
```
# The table above shows the desriptive statistics for the "Raw" data.
# But we want the results for variables such as leverage ratio, Cash to asset ratio, P
# So we have to create these variables from the "Raw" data.
```

Create Key Variables

We now need to create the variables we are interest in such as cash to asset ratio, profitability ratio (EBITDA to total assets) etc.

In [17]:
```
df2
```

Out[17]:

	ws_num	Year	TA	SALES_USD	MKT_EQUITY	BOOK_EQUITY	ST_DEBT	LT_DEBT	NPF
0	C036AAB00	2009	117.98	35.00	33.99	40.02	0.60	66.56	78.9
1	C036AAB00	2010	38.07	12.21	72.88	-25.37	0.62	59.03	7.5
2	C036AAB00	2011	36.60	15.09	41.71	-35.72	14.91	50.22	6.6
3	C036AAB00	2012	10.70	38.91	1.18	-24.37	0.08	31.21	0.6
4	C036ABF00	2007	934.71	108.52	449.35	403.75	21.30	226.76	697.7
...	...	...	...	...	...	...	...	...	
113280	C82699850	2013	255.16	461.95	852.48	148.53	0.00	0.00	19.1
113281	C82699850	2014	254.38	428.37	912.27	151.50	0.00	0.00	20.4
113282	C82699850	2015	267.09	435.81	766.49	153.45	0.00	0.00	23.2
113283	C82699850	2016	294.32	409.29	883.21	165.08	0.00	0.00	20.5
113284	C82699850	2017	307.89	478.27	980.09	166.75	0.00	0.00	27.1

96947 rows × 17 columns

In [18]:
```
df2['CASH']
```

Out[18]:
```
0         17.49
1         17.18
2         15.94
3          2.04
4        142.52
          ...
113280    73.02
113281    76.76
113282    78.31
113283    95.15
113284    92.37
Name: CASH, Length: 96947, dtype: float64
```

In [19]:
```
df2['TA']
```

Out[19]:
```
0        117.98
1         38.07
2         36.60
3         10.70
4        934.71
          ...
113280   255.16
113281   254.38
113282   267.09
113283   294.32
113284   307.89
Name: TA, Length: 96947, dtype: float64
```

In [20]:
```
CR = df2['CASH']/df2['TA']
```

In [21]:
```
CR
```

Out[21]:
```
0         0.15
1         0.45
2         0.44
3         0.19
4         0.15
          ...
113280    0.29
113281    0.30
113282    0.29
113283    0.32
113284    0.30
Length: 96947, dtype: float64
```

In [34]:
```
df2
```

Out[34]:

	ws_num	Year	TA	SALES_USD	MKT_EQUITY	BOOK_EQUITY	ST_DEBT	LT_DEBT	NPF
0	C036AAB00	2009	117.98	35.00	33.99	40.02	0.60	66.56	78.9
1	C036AAB00	2010	38.07	12.21	72.88	-25.37	0.62	59.03	7.5
2	C036AAB00	2011	36.60	15.09	41.71	-35.72	14.91	50.22	6.6
3	C036AAB00	2012	10.70	38.91	1.18	-24.37	0.08	31.21	0.6
4	C036ABF00	2007	934.71	108.52	449.35	403.75	21.30	226.76	697.7
...	...	...	...	...	...	...	...	...	
113280	C82699850	2013	255.16	461.95	852.48	148.53	0.00	0.00	19.1
113281	C82699850	2014	254.38	428.37	912.27	151.50	0.00	0.00	20.4
113282	C82699850	2015	267.09	435.81	766.49	153.45	0.00	0.00	23.2
113283	C82699850	2016	294.32	409.29	883.21	165.08	0.00	0.00	20.5
113284	C82699850	2017	307.89	478.27	980.09	166.75	0.00	0.00	27.1

96947 rows × 17 columns

In [36]:
```
# Create the key variables of interest
# We do not create leverage and Coverage variables here, but you can create it using t
#Leverage = df2((ST_DEBT + LT_DEBT) /TA)
#Coverage =  EBIT / INTEREST
# The coverage variable will generate infinity (inf) values when interest is zero.
# You should replace these 'inf' values with 'nan' as follows:
# df2['Coverage'] = df1['Coverage'].replace(np.inf, np.nan)
# Note: this assumes you have already created and added a variable called 'Coverage' t

# These are out X varibles or explnatory variables
df2['Tangibility']=df2['NPPE']/df2['TA']
df2['Market_to_book']= (df2['TA'] + df2['MKT_EQUITY'] - df2['BOOK_EQUITY']) /df2['TA']
#df2['Logsale'] = np.log(df2['TA'])
df2['Log_TA'] = np.log(df2['TA_USD'])
df2['Profitability']=df2['EBITDA']/df2['TA']

# We want to analyse cash to asset ratio (cash holding ratio)
df2['Cash_ratio'] = df2['CASH']/df2['TA']
```

In [37]:
```
df2
```

Out[37]:

	ws_num	Year	TA	SALES_USD	MKT_EQUITY	BOOK_EQUITY	ST_DEBT	LT_DEBT	NPF
0	C036AAB00	2009	117.98	35.00	33.99	40.02	0.60	66.56	78.9
1	C036AAB00	2010	38.07	12.21	72.88	-25.37	0.62	59.03	7.5
2	C036AAB00	2011	36.60	15.09	41.71	-35.72	14.91	50.22	6.6
3	C036AAB00	2012	10.70	38.91	1.18	-24.37	0.08	31.21	0.6
4	C036ABF00	2007	934.71	108.52	449.35	403.75	21.30	226.76	697.7
...	...	...	...	...	...	...	...	...	
113280	C82699850	2013	255.16	461.95	852.48	148.53	0.00	0.00	19.1
113281	C82699850	2014	254.38	428.37	912.27	151.50	0.00	0.00	20.4
113282	C82699850	2015	267.09	435.81	766.49	153.45	0.00	0.00	23.2
113283	C82699850	2016	294.32	409.29	883.21	165.08	0.00	0.00	20.5
113284	C82699850	2017	307.89	478.27	980.09	166.75	0.00	0.00	27.1

96947 rows × 22 columns

In [38]:
```
df2.shape
```

Out[38]:
```
(96947, 22)
```

In [39]:
```
df2.describe().T
```

Out[39]:

	count	mean	std	min	25%	50%	75%	max
Year	96947.00	2014.49	4.60	2007.00	2010.00	2015.00	2019.00	2022.00
TA	96947.00	163055.33	1250864.65	5.07	939.77	9049.64	44343.07	71461131.00
SALES_USD	96947.00	1731.15	9164.64	10.00	66.84	207.95	765.79	476914.94
MKT_EQUITY	96947.00	75136.90	455703.10	0.04	612.27	4208.74	20772.99	30622275.18
BOOK_EQUITY	96947.00	56079.54	344353.25	-552947.00	394.70	3911.00	20684.21	26245969.00
ST_DEBT	96054.00	19739.55	278141.34	0.00	7.55	370.82	3213.26	19748395.00
LT_DEBT	96482.00	31931.87	281304.45	-20398.00	4.92	312.00	3191.92	15308519.00
NPPE	96947.00	47294.90	322441.91	0.00	78.71	1625.31	11156.28	12775052.00
INTEREST	96947.00	721.39	9203.35	0.00	1.83	18.06	115.08	958000.00
EBIT	96947.00	7204.61	58343.36	-784440.00	8.67	327.11	2139.10	5977706.00
EBITDA	96947.00	12681.42	97086.12	-446328.00	27.75	573.92	3395.77	6803901.00
CASH	96947.00	25956.75	519448.46	0.00	109.90	1528.00	6954.85	71259671.00
TA_USD	96947.00	2834.52	17253.70	10.02	89.15	275.68	1010.47	1161546.63
NET_INCOME	96944.00	4020.26	41589.33	-1740738.00	2.68	175.42	1250.15	4957716.00
NATION	96947.00	410.98	204.42	36.00	344.00	392.00	392.00	826.00
Tangibility	96947.00	0.27	0.23	0.00	0.07	0.22	0.40	1.70
Market_to_book	96947.00	1.45	2.41	-0.05	0.83	1.03	1.46	426.72
Log_TA	96947.00	5.82	1.82	2.30	4.49	5.62	6.92	13.97
Profitability	96947.00	0.07	0.24	-17.58	0.04	0.08	0.13	22.74
Cash_ratio	96947.00	0.20	0.17	0.00	0.08	0.15	0.28	1.00

In [40]:
```
# We have too many variables
# We should keep only variables of interest
df3 = df2[["Tangibility", "Market_to_book", "Log_TA", "Profitability", "Cash_ratio", '
```

In [41]:
```
# The 'COUNTRY' Variable is not shown in the descrptive statistics because it is not c
# But it is in the dataframe, and we can use it to select subsamples of particular cou
df3
```

Out[41]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year	COUNTRY
0	0.67	0.95	4.56	-0.11	0.15	2009	Australia
1	0.20	3.58	3.47	-2.27	0.45	2010	Australia
2	0.18	3.12	3.67	-0.43	0.44	2011	Australia
3	0.06	3.39	2.39	-0.23	0.19	2012	Australia
4	0.75	1.05	6.71	-0.06	0.15	2007	Australia
...	...	...	...	...	...	...	...
113280	0.07	3.76	6.05	0.32	0.29	2013	UK
113281	0.08	3.99	5.98	0.30	0.30	2014	UK
113282	0.09	3.30	5.98	0.29	0.29	2015	UK
113283	0.07	3.44	5.89	0.30	0.32	2016	UK
113284	0.09	3.64	6.03	0.29	0.30	2017	UK

96947 rows × 7 columns

Select only the Australian observations

In [86]:
```
# bool = df3['COUNTRY'] == 'Australia'
# bool
# df_au = df3[bool]

df_au = df3[df3['COUNTRY'] == 'Australia']
df_au
```

Out[86]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year	COUNTRY
0	0.669	0.949	4.556	-0.107	0.148	2009	Australia
1	0.198	3.581	3.465	-2.275	0.451	2010	Australia
2	0.182	3.116	3.669	-0.432	0.436	2011	Australia
3	0.064	3.388	2.394	-0.228	0.190	2012	Australia
4	0.746	1.049	6.709	-0.059	0.152	2007	Australia
...	...	...	...	...	...	...	...
12088	0.516	1.377	10.364	0.264	0.016	2018	Australia
12089	0.525	1.735	10.304	0.189	0.018	2019	Australia
12090	0.553	1.513	10.329	0.200	0.015	2020	Australia
12091	0.558	1.710	10.369	0.180	0.041	2021	Australia
12092	0.563	1.701	10.264	0.176	0.032	2022	Australia

10278 rows × 7 columns

In [87]:
```
df_uk = df3[df3['COUNTRY'] == 'UK']
df_uk
```

Out[87]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year	COUNTRY
94020	0.437	1.111	6.555	0.157	0.007	2007	UK
94021	0.332	0.664	6.192	0.083	0.008	2008	UK
94022	0.056	0.809	6.149	-0.017	0.015	2009	UK
94023	0.053	0.771	6.113	0.088	0.014	2010	UK
94024	0.055	0.915	6.093	0.075	0.015	2011	UK
...	...	...	...	...	...	...	...
113280	0.075	3.759	6.046	0.319	0.286	2013	UK
113281	0.080	3.991	5.982	0.303	0.302	2014	UK
113282	0.087	3.295	5.976	0.295	0.293	2015	UK
113283	0.070	3.440	5.894	0.304	0.323	2016	UK
113284	0.088	3.642	6.031	0.290	0.300	2017	UK

14568 rows × 7 columns

In [88]:
```
df_au = df_au.dropna()
df_uk = df_uk.dropna()
```

In [89]:
```
df_au.shape
```

Out[89]:
```
(10278, 7)
```

In [90]:
```
df_uk.shape
```

Out[90]:
```
(14568, 7)
```

In [91]:
```
# Let's get the descriptive statistics for Australia

#df_au.describe().T

pd.set_option('display.float_format', '{:.3f}'.format)
df_au[["Tangibility", "Market_to_book", "Log_TA", "Profitability", "Cash_ratio"]].desc
```

Out[91]:

	count	mean	std	min	25%	50%	75%	max
Tangibility	10278.000	0.287	0.276	0.000	0.042	0.192	0.493	0.998
Market_to_book	10278.000	1.728	2.064	0.048	0.917	1.191	1.808	49.065
Log_TA	10278.000	5.452	1.819	2.306	4.017	5.210	6.638	11.885
Profitability	10278.000	0.075	0.384	-11.654	0.029	0.097	0.165	22.738
Cash_ratio	10278.000	0.146	0.164	0.000	0.037	0.087	0.191	0.999

In [92]:
```
# Let's get the descriptive statistics for UK

#df_uk.describe().T

pd.set_option('display.float_format', '{:.3f}'.format)
df_uk[["Tangibility", "Market_to_book", "Log_TA", "Profitability", "Cash_ratio"]].desc
```

Out[92]:

	count	mean	std	min	25%	50%	75%	max
Tangibility	14568.000	0.249	0.268	0.000	0.035	0.140	0.387	1.701
Market_to_book	14568.000	1.743	2.208	-0.055	0.970	1.284	1.910	91.201
Log_TA	14568.000	5.801	2.012	2.304	4.264	5.535	7.140	13.965
Profitability	14568.000	0.084	0.207	-4.643	0.039	0.094	0.154	8.758
Cash_ratio	14568.000	0.143	0.155	0.000	0.040	0.091	0.189	1.000

In [93]:
```
df_au.head()
```

Out[93]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year	COUNTRY
0	0.669	0.949	4.556	-0.107	0.148	2009	Australia
1	0.198	3.581	3.465	-2.275	0.451	2010	Australia
2	0.182	3.116	3.669	-0.432	0.436	2011	Australia
3	0.064	3.388	2.394	-0.228	0.190	2012	Australia
4	0.746	1.049	6.709	-0.059	0.152	2007	Australia

In [94]:
```
df_uk.head()
```

Out[94]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year	COUNTRY
94020	0.437	1.111	6.555	0.157	0.007	2007	UK
94021	0.332	0.664	6.192	0.083	0.008	2008	UK
94022	0.056	0.809	6.149	-0.017	0.015	2009	UK
94023	0.053	0.771	6.113	0.088	0.014	2010	UK
94024	0.055	0.915	6.093	0.075	0.015	2011	UK

In [47]:
```
# To remove outliers, we cap the variables at top and bottom 1%
# That means at 0.01 and 0.99 quantiles
df_au1=df_au.loc[:, df_au.columns != 'COUNTRY']
df_au1=df_au1.dropna()
df_au1 = df_au1.clip(lower=df_au1.quantile(0.01), upper=df_au1.quantile(0.99), axis=1)

df_au1.describe().T
```

Out[47]:

	count	mean	std	min	25%	50%	75%	max
Tangibility	10278.000	0.287	0.276	0.000	0.042	0.192	0.493	0.936
Market_to_book	10278.000	1.659	1.396	0.459	0.917	1.191	1.808	9.148
Log_TA	10278.000	5.446	1.799	2.475	4.017	5.210	6.638	9.974
Profitability	10278.000	0.079	0.187	-0.730	0.029	0.097	0.165	0.541
Cash_ratio	10278.000	0.145	0.160	0.001	0.037	0.087	0.191	0.767
Year	10278.000	2014.340	4.651	2007.000	2010.000	2014.000	2018.000	2022.000

In [95]:
```
# To remove outliers, we cap the variables at top and bottom 1%
# That means at 0.01 and 0.99 quantiles
df_uk1=df_uk.loc[:, df_au.columns != 'COUNTRY']
df_uk1=df_uk1.dropna()
df_uk1 = df_uk1.clip(lower=df_au1.quantile(0.01), upper=df_au1.quantile(0.99), axis=1)

df_uk1.describe().T
```

Out[95]:

	count	mean	std	min	25%	50%	75%	max
Tangibility	14568.000	0.249	0.267	0.000	0.035	0.140	0.387	0.936
Market_to_book	14568.000	1.684	1.260	0.459	0.970	1.284	1.910	9.144
Log_TA	14568.000	5.769	1.927	2.475	4.264	5.535	7.140	9.973
Profitability	14568.000	0.084	0.149	-0.729	0.039	0.094	0.154	0.541
Cash_ratio	14568.000	0.142	0.151	0.001	0.040	0.091	0.189	0.766
Year	14568.000	2013.775	4.536	2007.000	2010.000	2014.000	2018.000	2022.000

In [48]:
```
# This is the unclipped distribution
df_au.quantile([0, 0.01, 0.25, 0.5, 0.75, 0.99, 1])
```

Out[48]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
0.000	0.000	0.048	2.306	-11.654	0.000	2007.000
0.010	0.000	0.459	2.475	-0.730	0.001	2007.000
0.250	0.042	0.917	4.017	0.029	0.037	2010.000
0.500	0.192	1.191	5.210	0.097	0.087	2014.000
0.750	0.493	1.808	6.638	0.165	0.191	2018.000
0.990	0.936	9.148	9.974	0.541	0.767	2022.000
1.000	0.998	49.065	11.885	22.738	0.999	2022.000

In [96]:
```
# This is the unclipped distribution
df_uk.quantile([0, 0.01, 0.25, 0.5, 0.75, 0.99, 1])
```

Out[96]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
0.000	0.000	-0.055	2.304	-4.643	0.000	2007.000
0.010	0.000	0.504	2.473	-0.520	0.000	2007.000
0.250	0.035	0.970	4.264	0.039	0.040	2010.000
0.500	0.140	1.284	5.535	0.094	0.091	2014.000
0.750	0.387	1.910	7.140	0.154	0.189	2018.000
0.990	0.951	7.803	11.145	0.439	0.746	2022.000
1.000	1.701	91.201	13.965	8.758	1.000	2022.000

In [49]:
```
# This is the clipped distribution which has replaced the outliers
df_au1.quantile([0, 0.01, 0.25, 0.5, 0.75, 0.99, 1])
```

Out[49]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
0.000	0.000	0.459	2.475	-0.730	0.001	2007.000
0.010	0.000	0.459	2.475	-0.729	0.001	2007.000
0.250	0.042	0.917	4.017	0.029	0.037	2010.000
0.500	0.192	1.191	5.210	0.097	0.087	2014.000
0.750	0.493	1.808	6.638	0.165	0.191	2018.000
0.990	0.936	9.144	9.973	0.541	0.766	2022.000
1.000	0.936	9.148	9.974	0.541	0.767	2022.000

In [97]:
```
# This is the clipped distribution which has replaced the outliers
df_uk1.quantile([0, 0.01, 0.25, 0.5, 0.75, 0.99, 1])
```

Out[97]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
0.000	0.000	0.459	2.475	-0.729	0.001	2007.000
0.010	0.000	0.504	2.475	-0.520	0.001	2007.000
0.250	0.035	0.970	4.264	0.039	0.040	2010.000
0.500	0.140	1.284	5.535	0.094	0.091	2014.000
0.750	0.387	1.910	7.140	0.154	0.189	2018.000
0.990	0.936	7.803	9.973	0.439	0.746	2022.000
1.000	0.936	9.144	9.973	0.541	0.766	2022.000

In [50]:
```
df_au1.describe().T
```

Out[50]:

	count	mean	std	min	25%	50%	75%	max
Tangibility	10278.000	0.287	0.276	0.000	0.042	0.192	0.493	0.936
Market_to_book	10278.000	1.659	1.396	0.459	0.917	1.191	1.808	9.148
Log_TA	10278.000	5.446	1.799	2.475	4.017	5.210	6.638	9.974
Profitability	10278.000	0.079	0.187	-0.730	0.029	0.097	0.165	0.541
Cash_ratio	10278.000	0.145	0.160	0.001	0.037	0.087	0.191	0.767
Year	10278.000	2014.340	4.651	2007.000	2010.000	2014.000	2018.000	2022.000

In [98]:
```
df_uk1.describe().T
```

Out[98]:

	count	mean	std	min	25%	50%	75%	max
Tangibility	14568.000	0.249	0.267	0.000	0.035	0.140	0.387	0.936
Market_to_book	14568.000	1.684	1.260	0.459	0.970	1.284	1.910	9.144
Log_TA	14568.000	5.769	1.927	2.475	4.264	5.535	7.140	9.973
Profitability	14568.000	0.084	0.149	-0.729	0.039	0.094	0.154	0.541
Cash_ratio	14568.000	0.142	0.151	0.001	0.040	0.091	0.189	0.766
Year	14568.000	2013.775	4.536	2007.000	2010.000	2014.000	2018.000	2022.000

Boxplot

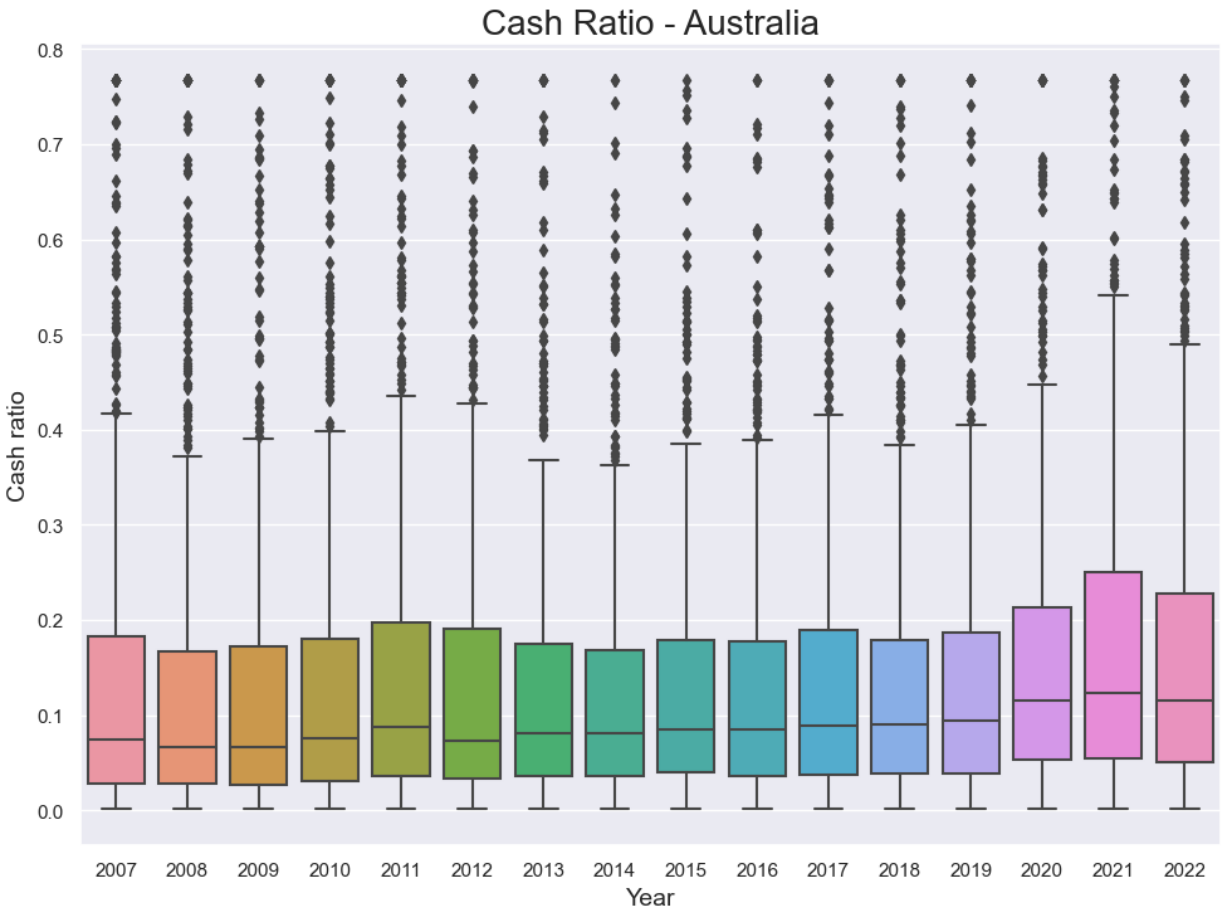
The Boxplot shows the distribution of a variable.

You can learn more about Boxplot from the following website:

https://www.geeksforgeeks.org/box-plot-visualization-with-pandas-and-seaborn/

In [51]:
```
with sns.axes_style(style=None):
    fig, ax = plt.subplots()
    fig.set_size_inches(11.7, 8.27)
    sns.boxplot("Year","Cash_ratio",data=df_au1,ax=ax)

    ax.set_xlabel('Year', fontsize=14)
    ax.set_ylabel('Cash ratio', fontsize=14)
    ax.set_title('Cash Ratio - Australia', fontsize=20)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

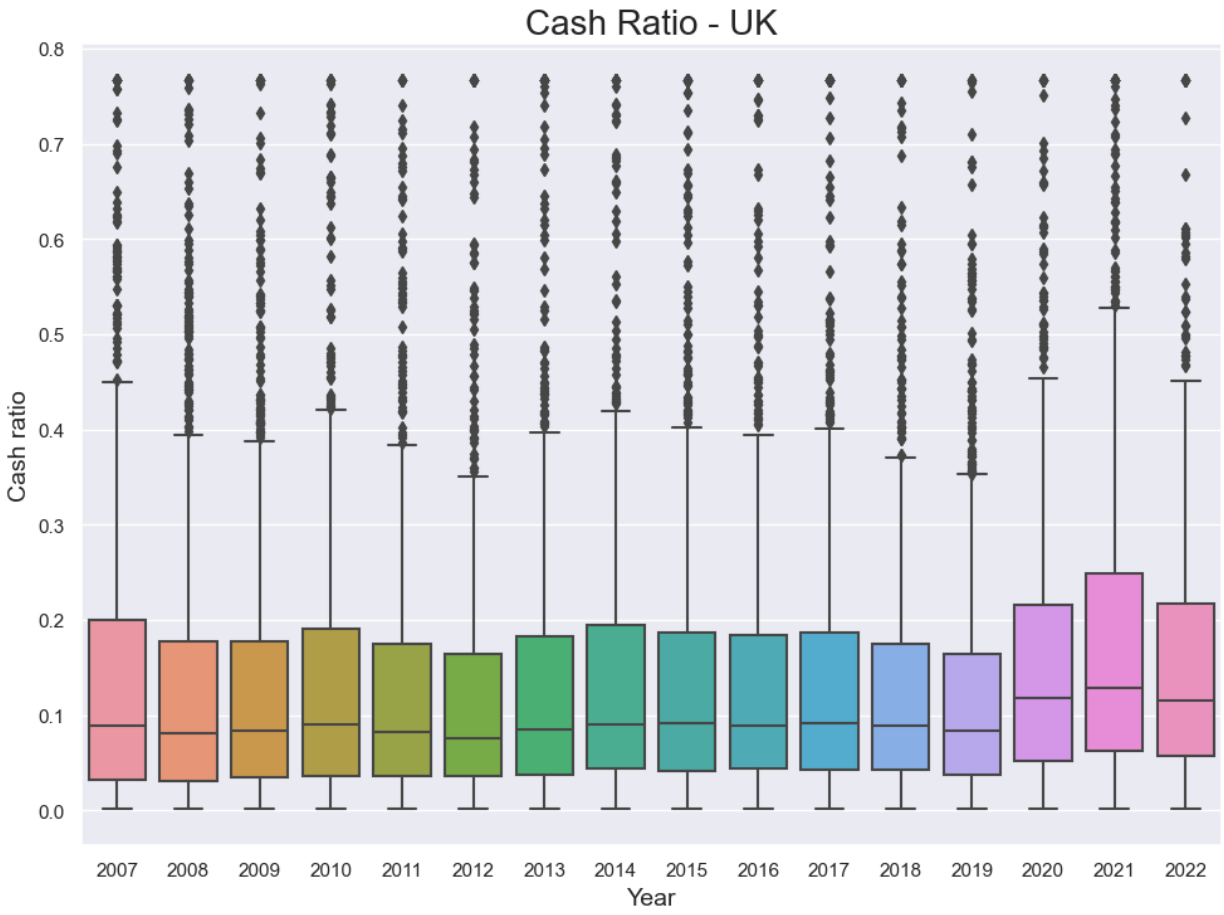


Interpretations:

- The line in the middle of the boxes is the median of the 5oth percentile value of the variable (Cash_ratio).
- The box plot shows that the median cash holding ratio is less than 0.1 or 10% for all the years.
- The ratio has increased since 2012 and is close to 10% by 2017.
- The 75the percentile (75%) values (upper edge of the box) is less that 0.2 or 20% for all the years.
- 2011 had the highest 75 percentile value for the cash ratio and it was then about 20%.
- The many dots on the top part of the graphs show that there are many large values or outliers in the Cash ratio.

In [99]:
```
with sns.axes_style(style=None):
    fig, ax = plt.subplots()
    fig.set_size_inches(11.7, 8.27)
    sns.boxplot("Year","Cash_ratio",data=df_uk1,ax=ax)

    ax.set_xlabel('Year', fontsize=14)
    ax.set_ylabel('Cash ratio', fontsize=14)
    ax.set_title('Cash Ratio - UK', fontsize=20)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

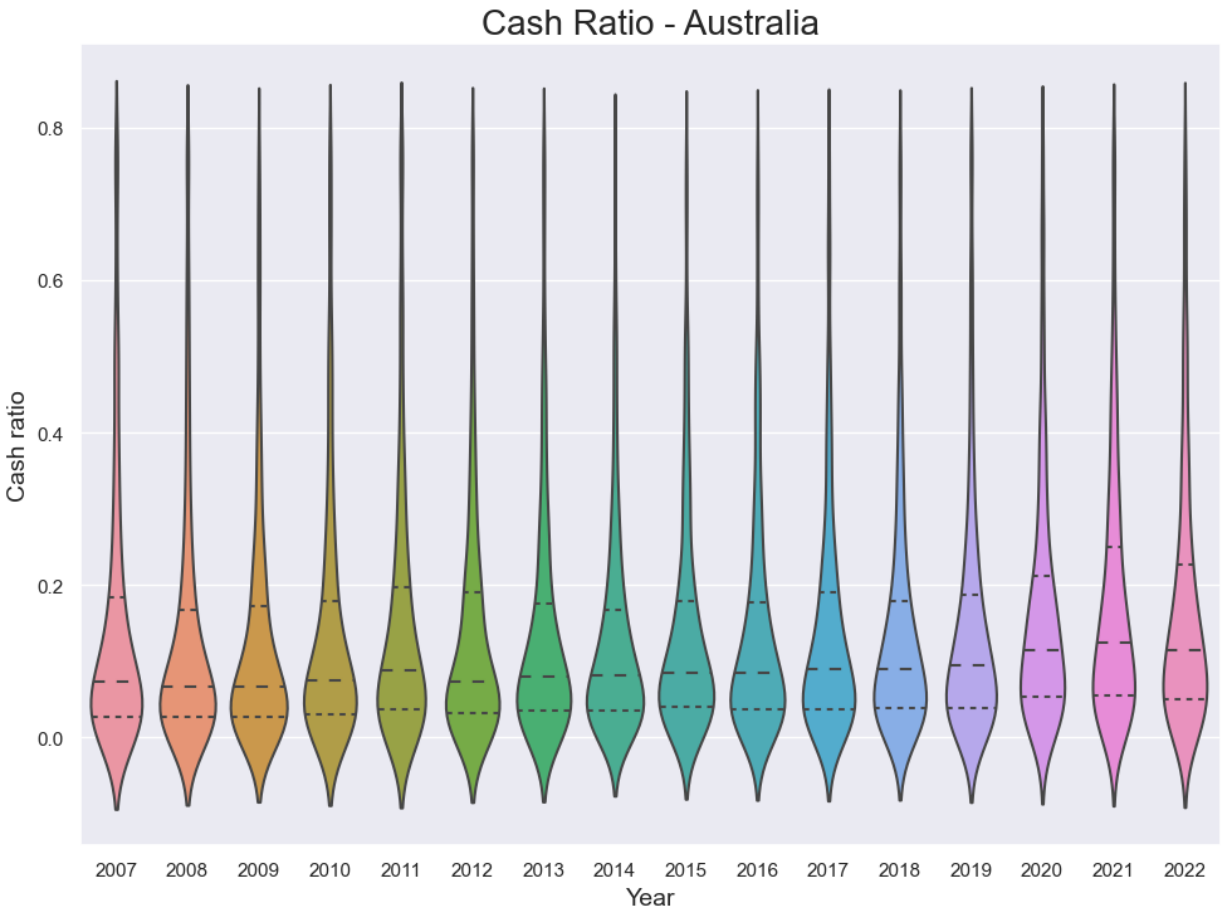


In [ ]:

Violinplot

In [52]:
```
with sns.axes_style(style=None):
    fig, ax = plt.subplots()
    fig.set_size_inches(11.7, 8.27)
    sns.violinplot("Year","Cash_ratio",data=df_au1,split='True', inner="quartile",ax=a

    ax.set_xlabel('Year', fontsize=14)
    ax.set_ylabel('Cash ratio', fontsize=14)
    ax.set_title('Cash Ratio - Australia', fontsize=20)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



Calculate the Distribution of Cash Ratios over time

We use the quantile() method and mean() method to calculate the distribution of the cash ratio.

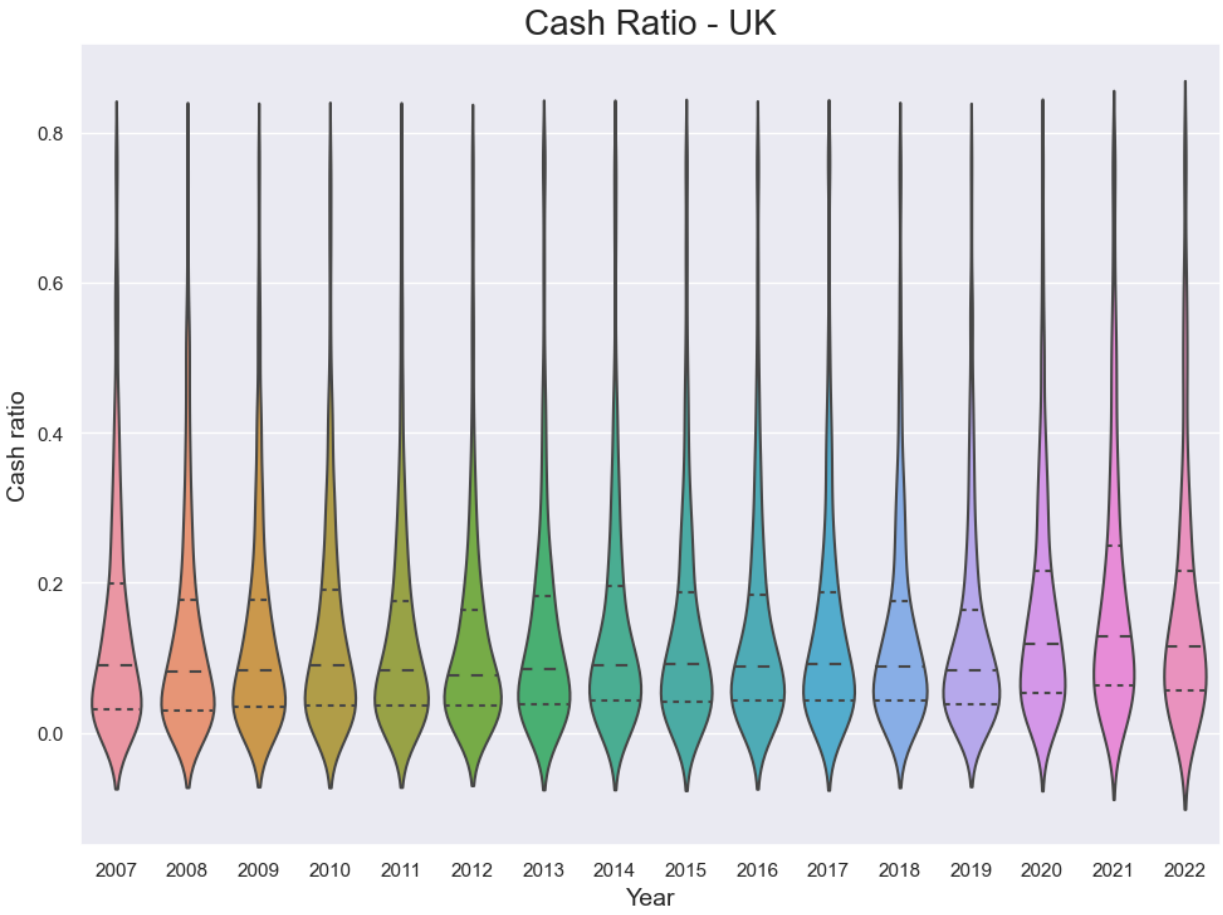
Here we use these methods on grouped data.

So we use the groupby operation first to group the data.

In [100…

```
with sns.axes_style(style=None):
    fig, ax = plt.subplots()
    fig.set_size_inches(11.7, 8.27)
    sns.violinplot("Year","Cash_ratio",data=df_uk1,split='True', inner="quartile",ax=a

    ax.set_xlabel('Year', fontsize=14)
    ax.set_ylabel('Cash ratio', fontsize=14)
    ax.set_title('Cash Ratio - UK', fontsize=20)
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



In [105…

```
g_df1 = df_au1[['Year', 'Cash_ratio']]

g_df1 = g_df1.groupby('Year')

quantiles = g_df1['Cash_ratio'].quantile([0.10, 0.25, 0.5, 0.75, 0.90]).unstack()
mean = g_df1['Cash_ratio'].agg(['mean'])

data_combined=pd.concat([quantiles, mean], 1)
data_stacked_au=data_combined.stack().reset_index(name='Cash_ratio').rename(columns={'

# Let's look at how
data_stacked_au
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_18436\2603797947.py:8: FutureWarning: In a f
uture version of pandas all arguments of concat except for the argument 'objs' will b
e keyword-only.
  data_combined=pd.concat([quantiles, mean], 1)
```

Out[105]:

	Year	Quantiles and Mean	Cash_ratio
0	2007	0.100	0.011
1	2007	0.250	0.027
2	2007	0.500	0.074
3	2007	0.750	0.183
4	2007	0.900	0.402
...	...	...	...
91	2022	0.250	0.051
92	2022	0.500	0.115
93	2022	0.750	0.228
94	2022	0.900	0.411
95	2022	mean	0.169

96 rows × 3 columns

In [106…

```
g_df1 = df_uk1[['Year', 'Cash_ratio']]

g_df1 = g_df1.groupby('Year')

quantiles = g_df1['Cash_ratio'].quantile([0.10, 0.25, 0.5, 0.75, 0.90]).unstack()
mean = g_df1['Cash_ratio'].agg(['mean'])

data_combined=pd.concat([quantiles, mean], 1)
data_stacked_uk=data_combined.stack().reset_index(name='Cash_ratio').rename(columns={'

# Let's look at how
data_stacked_uk
```

```
C:\Users\HP\AppData\Local\Temp\ipykernel_18436\3509911312.py:8: FutureWarning: In a f
uture version of pandas all arguments of concat except for the argument 'objs' will b
e keyword-only.
  data_combined=pd.concat([quantiles, mean], 1)
```

Out[106]:

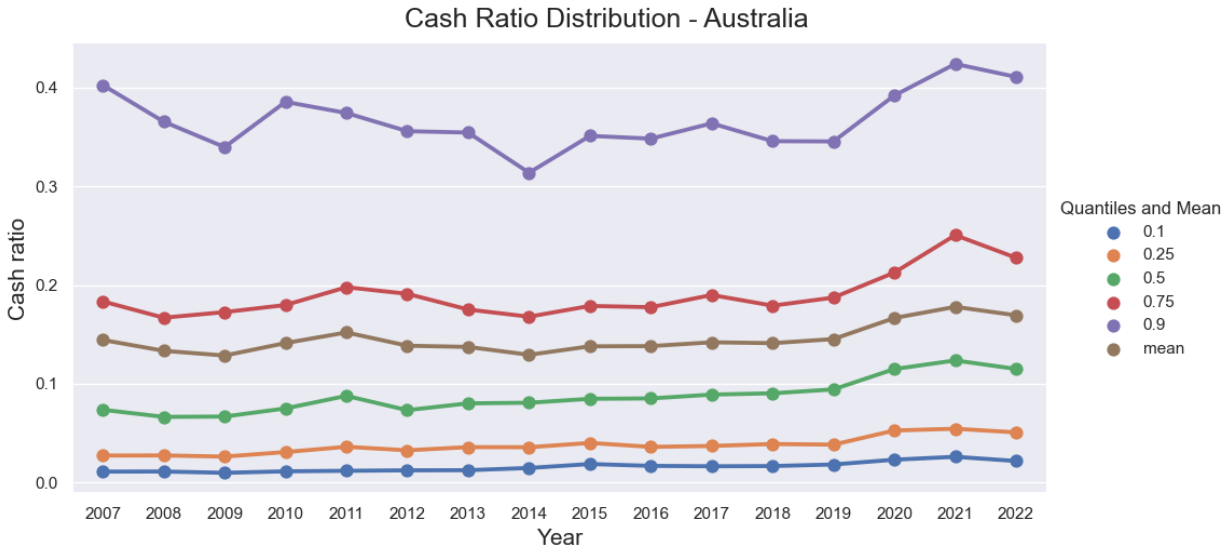
	Year	Quantiles and Mean	Cash_ratio
0	2007	0.100	0.009
1	2007	0.250	0.031
2	2007	0.500	0.089
3	2007	0.750	0.199
4	2007	0.900	0.360
...	...	...	...
91	2022	0.250	0.057
92	2022	0.500	0.115
93	2022	0.750	0.216
94	2022	0.900	0.405
95	2022	mean	0.168

96 rows × 3 columns

Plot the Distribution of Cash Ratios over time using Catplot

In [108…

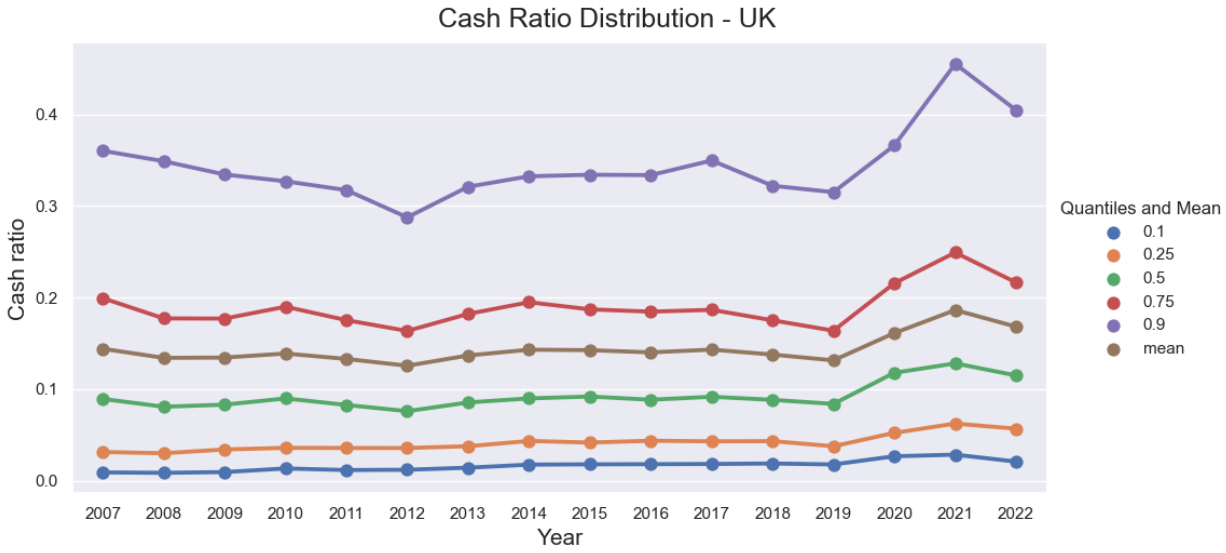
```
# Catplot
ax = sns.catplot(x="Year", y="Cash_ratio", hue="Quantiles and Mean", kind="point", dat
        height=5, # make the plot 5 units high
        aspect=2); # height should be three times width

ax.fig.suptitle('Cash Ratio Distribution - Australia',fontsize=18,y=1.03);
plt.xlabel('Year', fontsize=15);
plt.ylabel('Cash ratio', fontsize=15);
```



In [109…

```
# Catplot
ax = sns.catplot(x="Year", y="Cash_ratio", hue="Quantiles and Mean", kind="point", dat
        height=5, # make the plot 5 units high
```

```
        aspect=2); # height should be three times width

ax.fig.suptitle('Cash Ratio Distribution - UK',fontsize=18,y=1.03);
plt.xlabel('Year', fontsize=15);
plt.ylabel('Cash ratio', fontsize=15);
```



Using jointplot() to explore the relationship between firm characterstics and Cash ratio

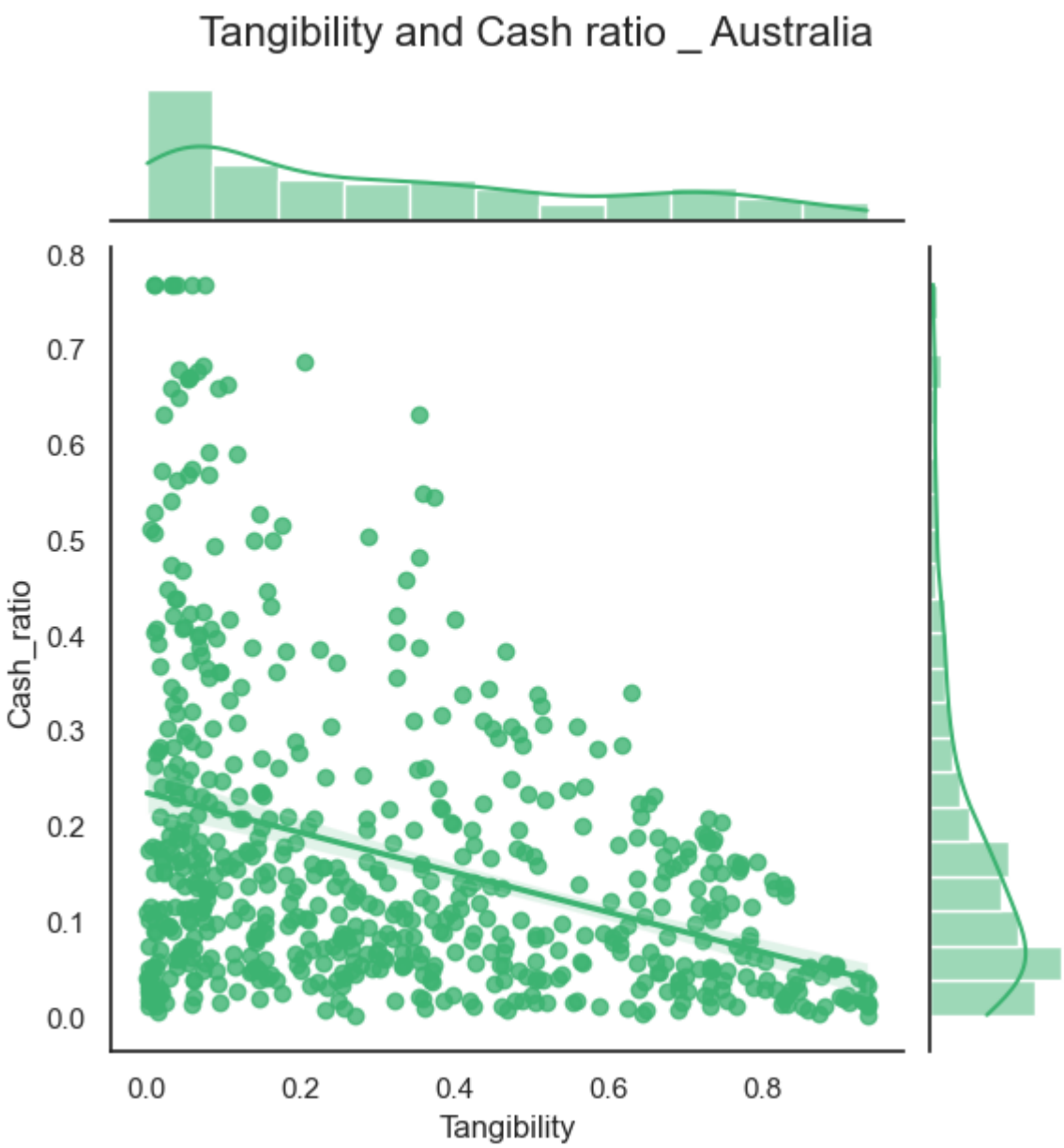
Explore the relation between Tangibility and Cash ratio

We do this analysis using only the 2020 data

In [112…

```
# Select the observations for 2020
df_au_2020 = df_au1[df_au1['Year'] == 2020]

# Plot using jointplot()
with sns.axes_style('white'):
    p = sns.jointplot("Tangibility","Cash_ratio", data=df_au_2020, kind='reg',color='r
    p.fig.suptitle("Tangibility and Cash ratio _ Australia",fontsize=16,y=1.03)

    plt.xlabel('Tangibility', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
   # plt.savefig('C:/Users/User/Desktop/jointplot_1.png')
    plt.show()
```

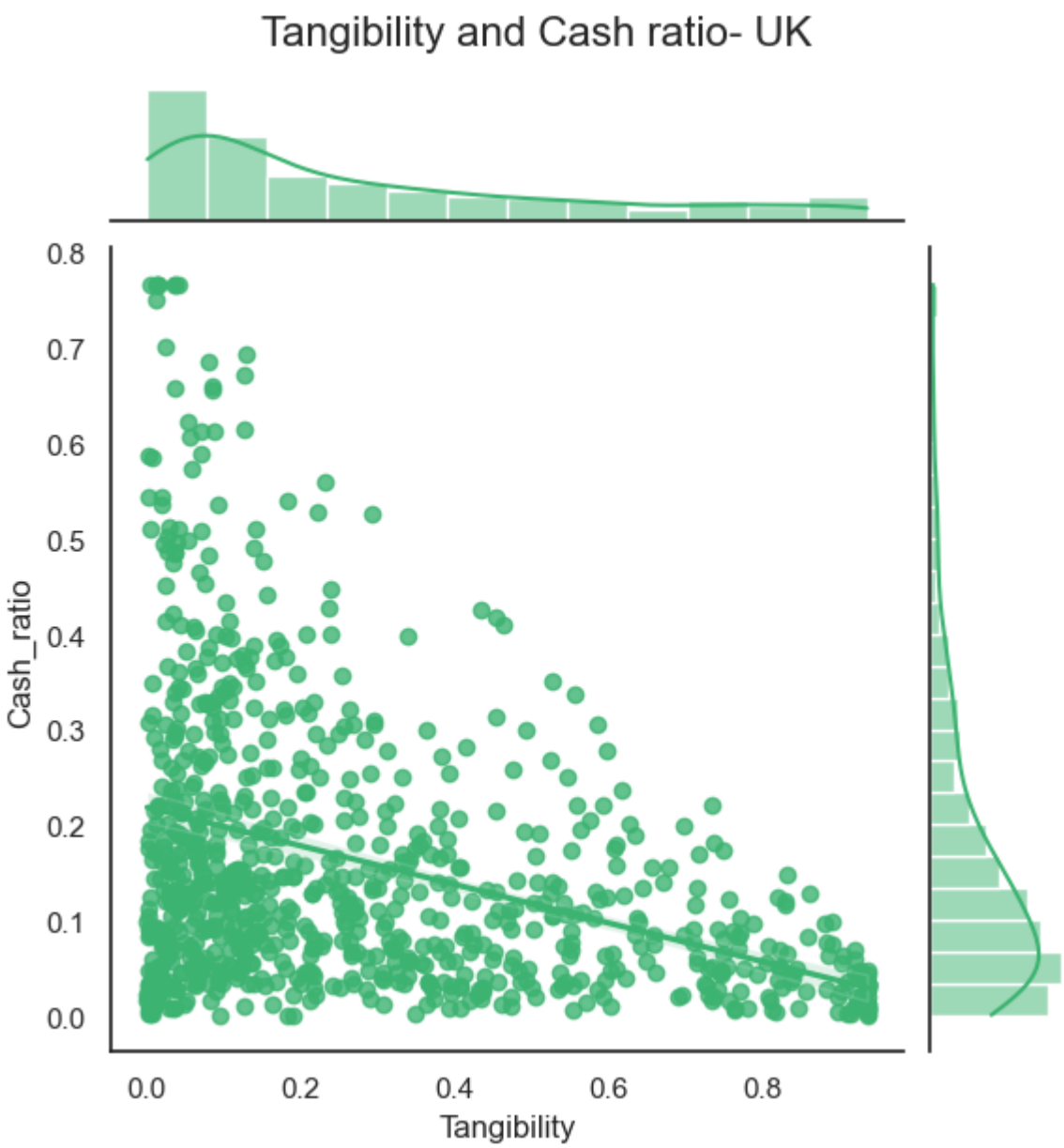
```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



In [113…

```
# Select the observations for 2020
df_uk_2020 = df_uk1[df_uk1['Year'] == 2020]

# Plot using jointplot()
with sns.axes_style('white'):
    p = sns.jointplot("Tangibility","Cash_ratio", data=df_uk_2020, kind='reg',color='r
    p.fig.suptitle("Tangibility and Cash ratio- UK",fontsize=16,y=1.03)

    plt.xlabel('Tangibility', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
   # plt.savefig('C:/Users/User/Desktop/jointplot_1.png')
    plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



The scatter plot and the regression line above shows a negative relation between Asset Tangibilty and Cash Ratio

We can do similar plots for the other firm characteristics

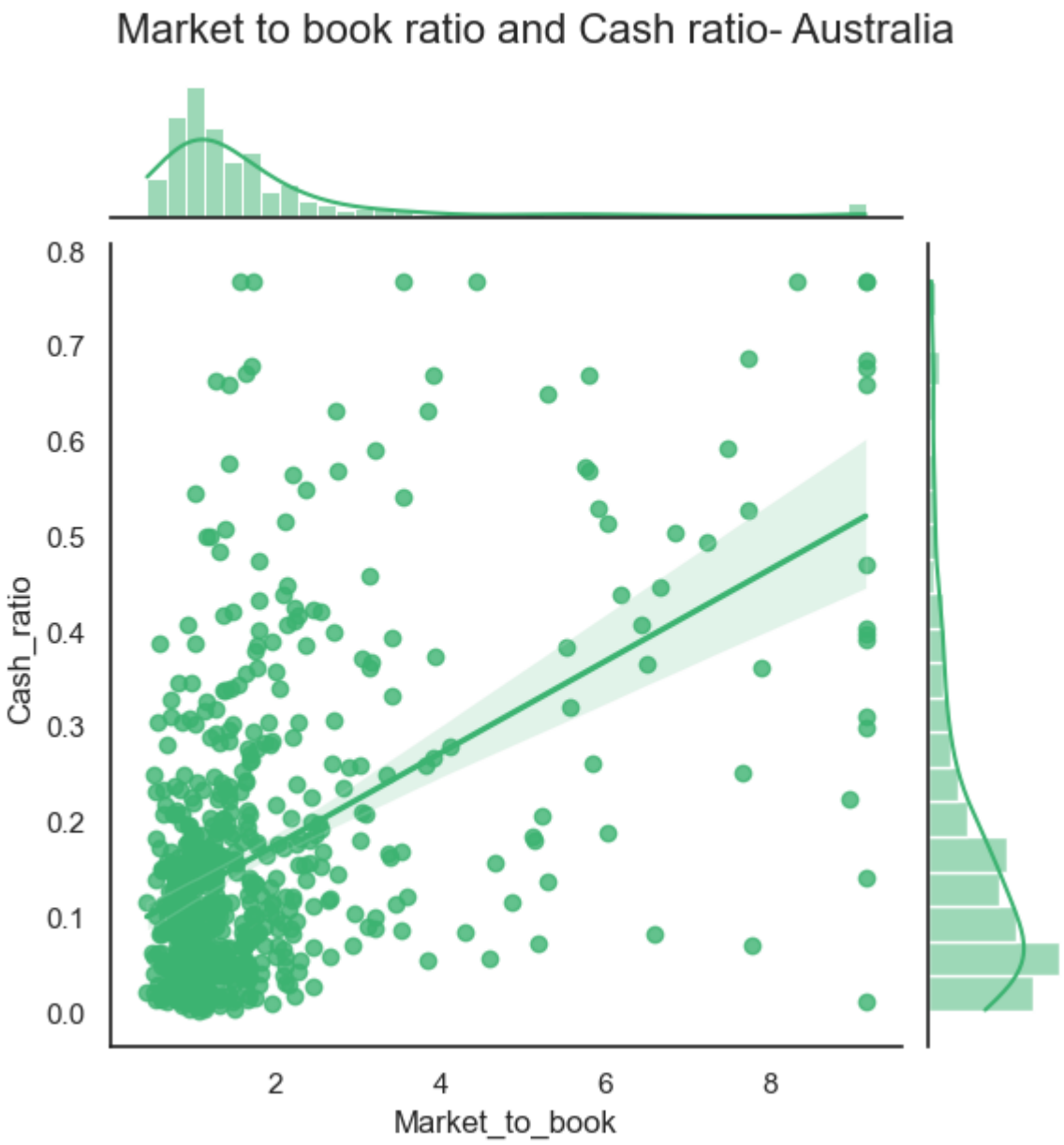
Explore the relation between Market to book ratio and Cash ratio

In [114…

```
# Select the observations for 2020
df_au_2020 = df_au1[df_au1['Year'] == 2020]

with sns.axes_style('white'):
    p = sns.jointplot("Market_to_book","Cash_ratio", data=df_au_2020, kind='reg',color
    p.fig.suptitle("Market to book ratio and Cash ratio- Australia",fontsize=16,y=1.03
```

```
    plt.xlabel('Market to book ratio', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
    plt.show()
```

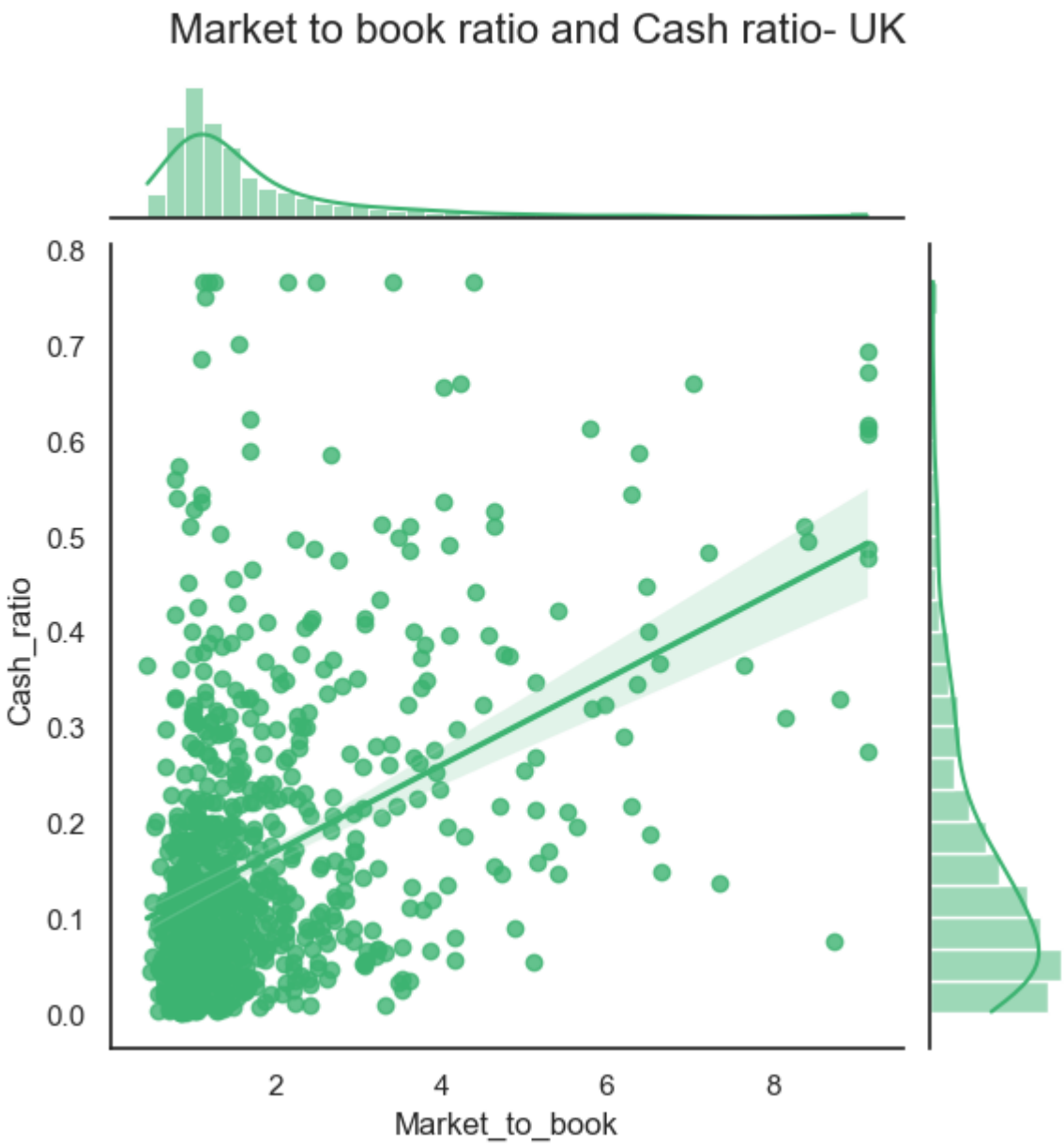
```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



In [115…

```
# Select the observations for 2020
df_uk_2020 = df_uk1[df_uk1['Year'] == 2020]

with sns.axes_style('white'):
    p = sns.jointplot("Market_to_book","Cash_ratio", data=df_uk_2020, kind='reg',color
    p.fig.suptitle("Market to book ratio and Cash ratio- UK",fontsize=16,y=1.03)

    plt.xlabel('Market to book ratio', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
    plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



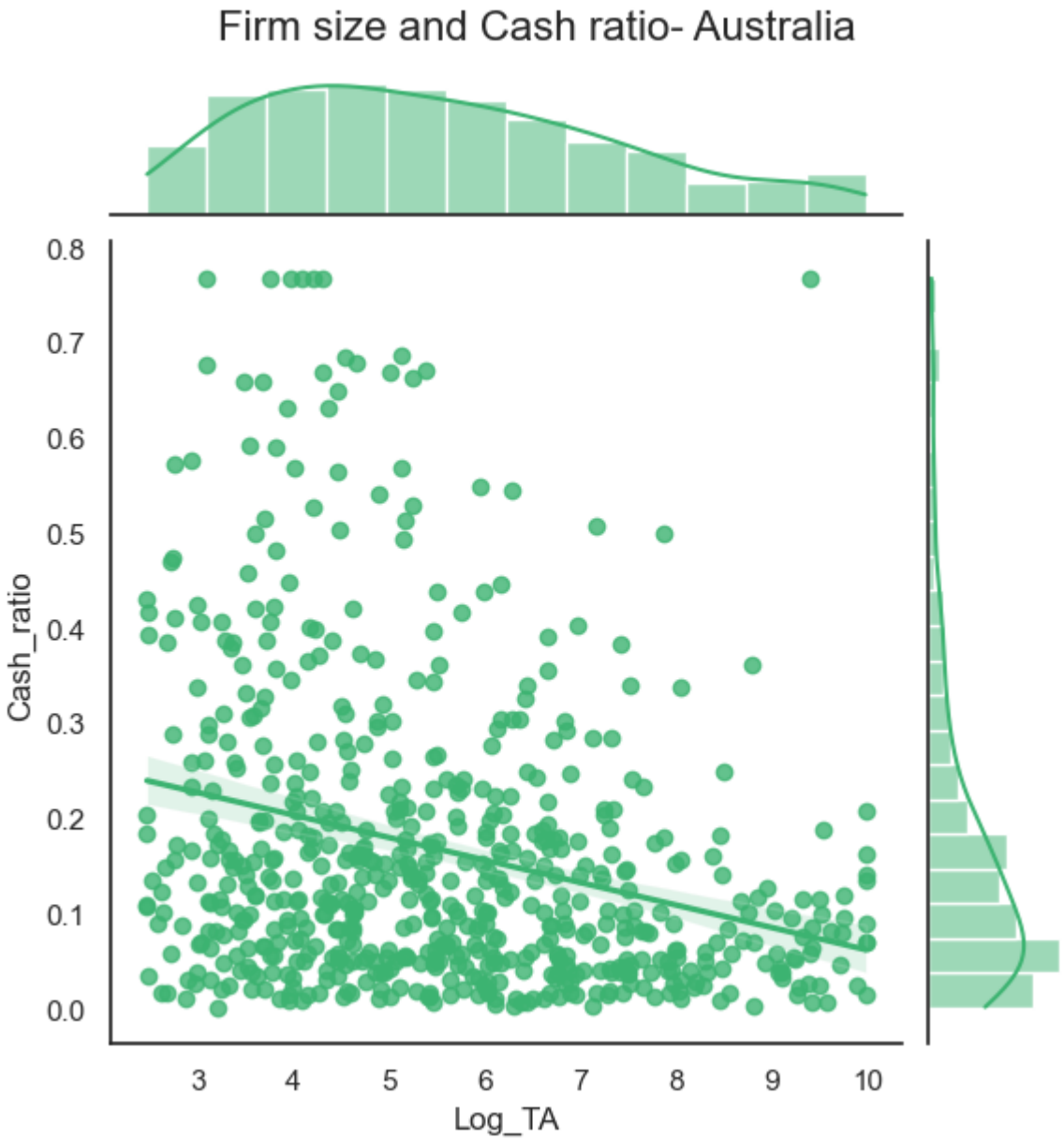
Explore the relation between Firm size (Log_TA) and Cash ratio

In [117…

```
# Select the observations for 2020
df_au_2020 = df_au1[df_au1['Year'] == 2020]

with sns.axes_style('white'):
    p = sns.jointplot("Log_TA","Cash_ratio", data=df_au_2020, kind='reg',color='mediu

    p.fig.suptitle("Firm size and Cash ratio- Australia",fontsize=16,y=1.03)

    plt.xlabel('Firm size (log of Total Assets)', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
```

```
    plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

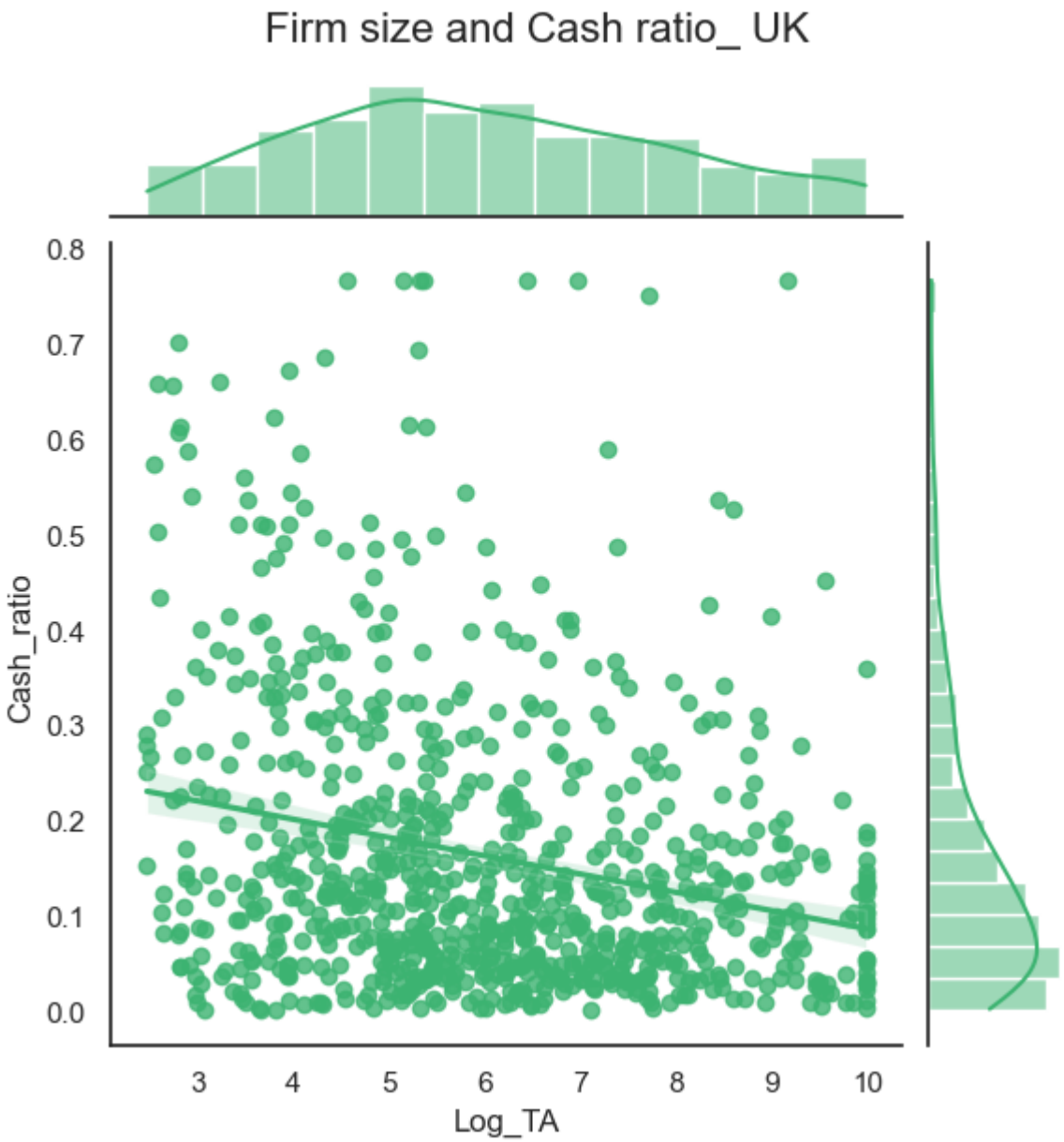


In [118…

```
# Select the observations for 2020
df_uk_2020 = df_uk1[df_uk1['Year'] == 2020]

with sns.axes_style('white'):
    p = sns.jointplot("Log_TA","Cash_ratio", data=df_uk_2020, kind='reg',color='mediu

    p.fig.suptitle("Firm size and Cash ratio_ UK",fontsize=16,y=1.03)

    plt.xlabel('Firm size (log of Total Assets)', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
```

```
    plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



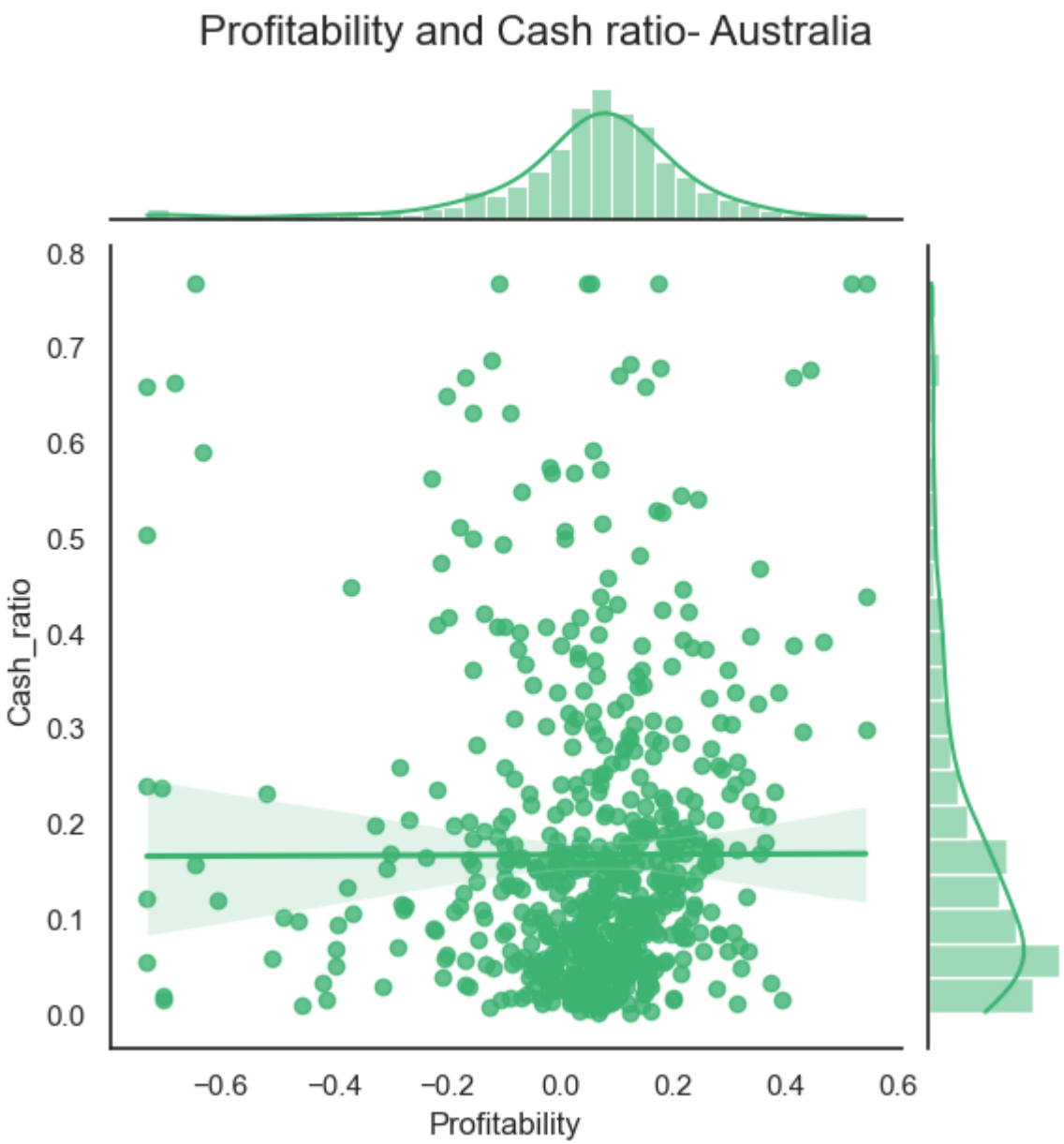
Explore the relation between Profitability and Cash ratio

In [122…

```
# Select the observations for 2020
df_au_2020 = df_au1[df_au1['Year'] == 2020]

with sns.axes_style('white'):
    p = sns.jointplot("Profitability","Cash_ratio", data=df_au_2020, kind='reg',color=
    p.fig.suptitle("Profitability and Cash ratio- Australia",fontsize=16,y=1.03)

    plt.xlabel('Profitability', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
```

```
    plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```

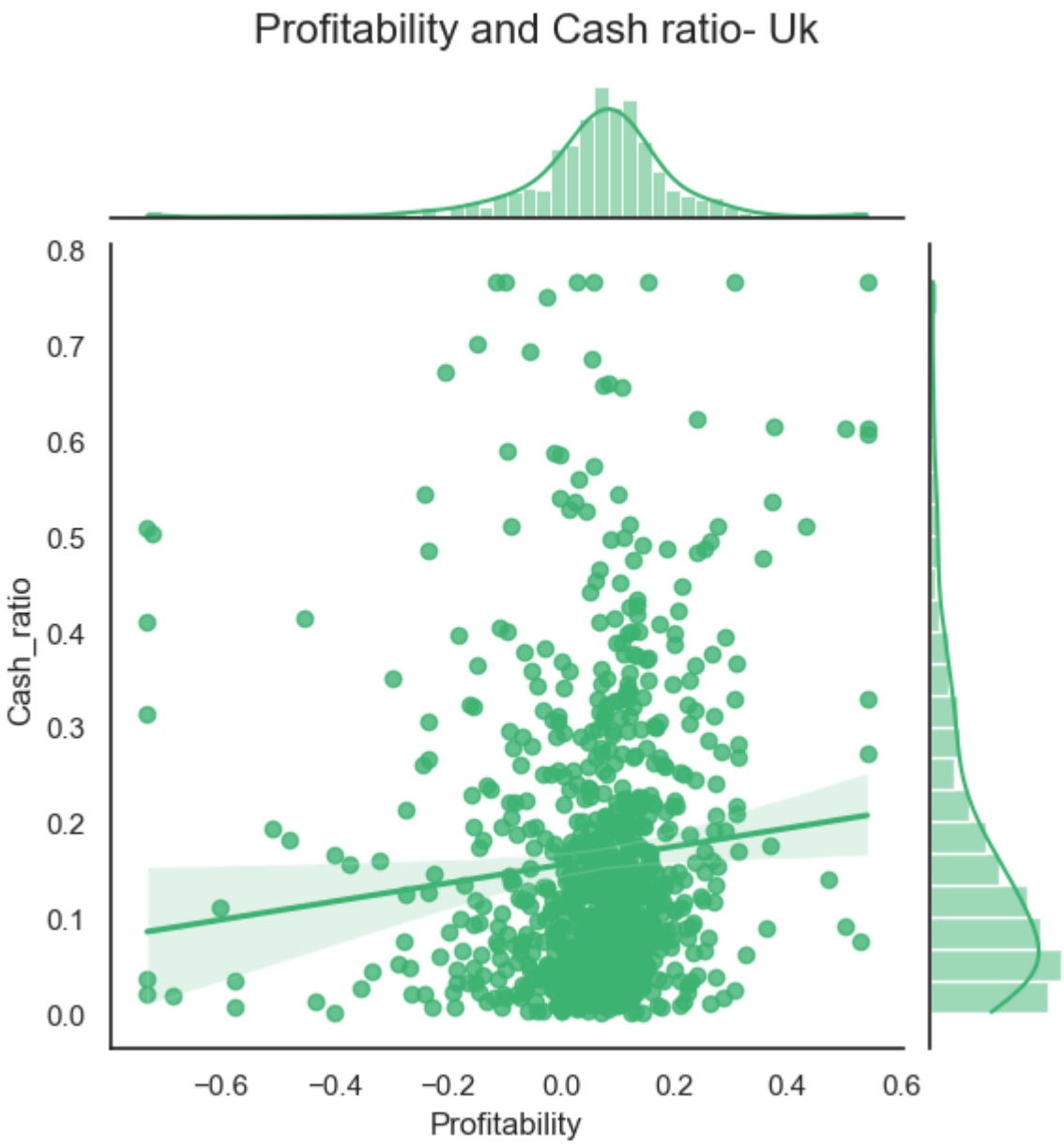


In [119…

```
# Select the observations for 2020
df_uk_2020 = df_uk1[df_uk1['Year'] == 2020]

with sns.axes_style('white'):
    p = sns.jointplot("Profitability","Cash_ratio", data=df_uk_2020, kind='reg',color=
    p.fig.suptitle("Profitability and Cash ratio- Uk",fontsize=16,y=1.03)

    plt.xlabel('Profitability', fontsize=13)
    plt.ylabel('Cash ratio', fontsize=13)
```

```
    plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pas
s the following variables as keyword args: x, y. From version 0.12, the only valid po
sitional argument will be `data`, and passing other arguments without an explicit key
word will result in an error or misinterpretation.
  warnings.warn(
```



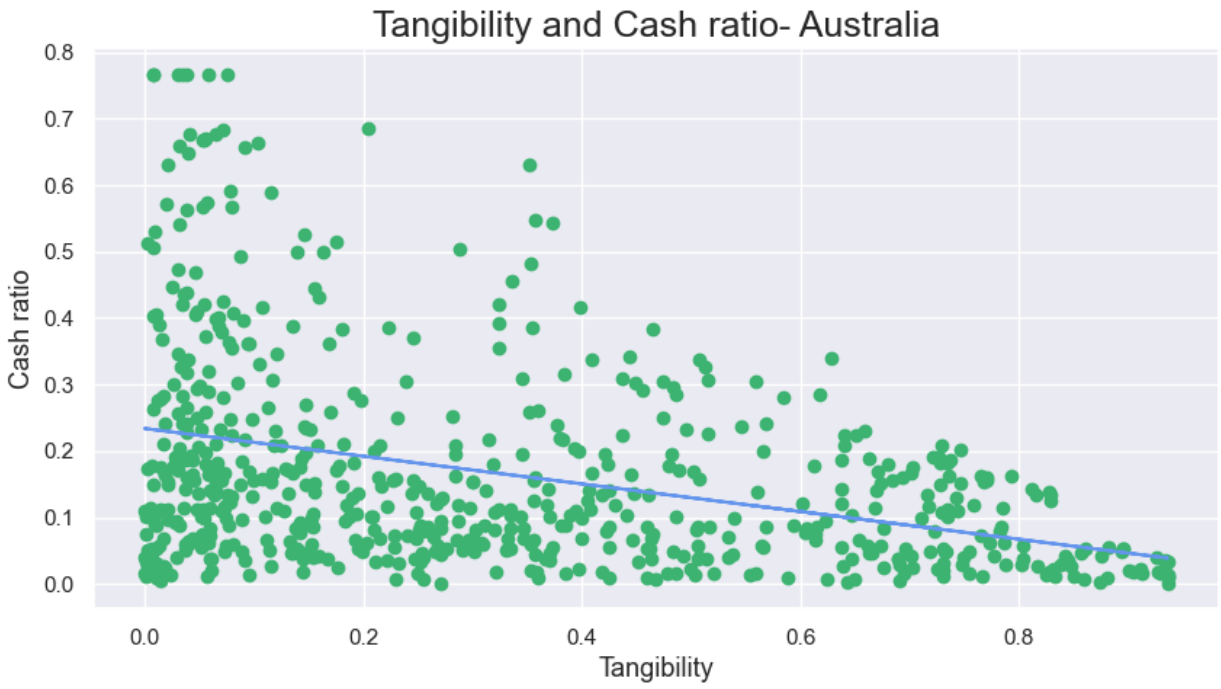
Regression and Scatter Plot using LinearRegression

We can also get a scatter plot and regression line from LinearRegression from ScikitLearn library, which we covered in the machine learning lecture

In [123…

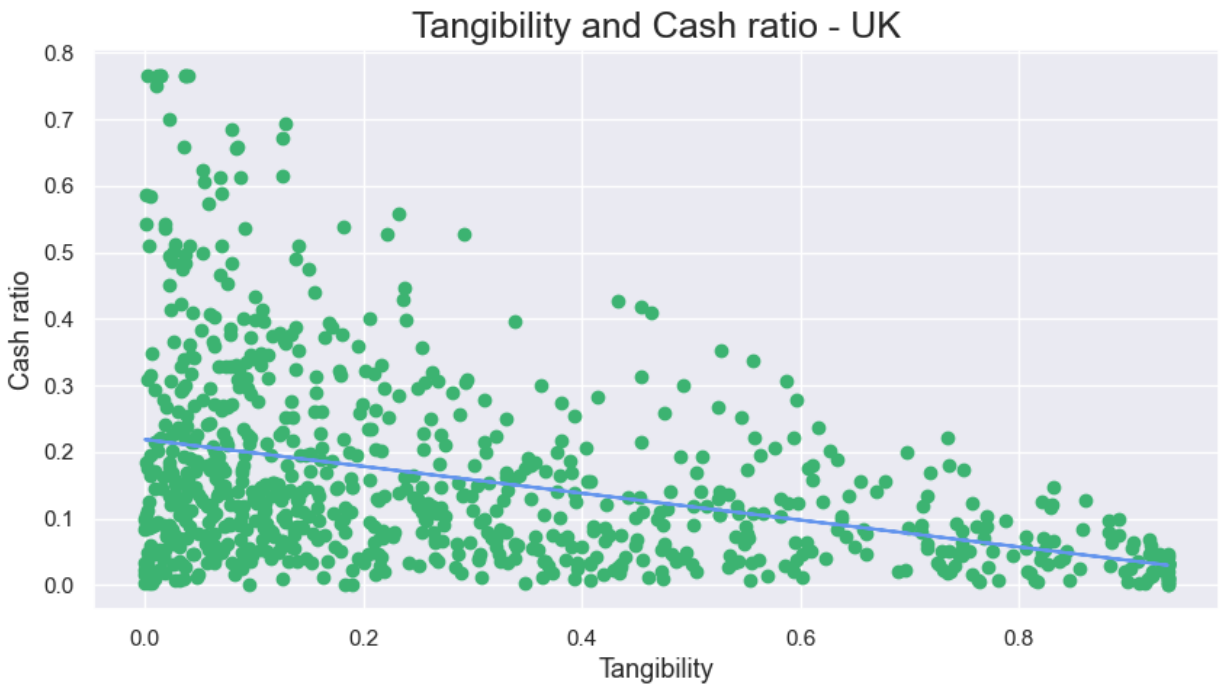
```
from sklearn.linear_model import LinearRegression

X = df_au_2020["Tangibility"].values.reshape(-1, 1)  # values converts it into a numpy
y = df_au_2020["Cash_ratio"].values.reshape(-1, 1)  # -1 means that calculate the dime
```

```
linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions

plt.figure(figsize=(10,5))
plt.scatter(X, y,color='mediumseagreen')
plt.plot(X, Y_pred, color='cornflowerblue')

plt.title('Tangibility and Cash ratio- Australia', fontsize=18);
plt.xlabel('Tangibility', fontsize=13)
plt.ylabel('Cash ratio', fontsize=13)
plt.show()
```



In [124…

```
from sklearn.linear_model import LinearRegression

X = df_uk_2020["Tangibility"].values.reshape(-1, 1)  # values converts it into a numpy
y = df_uk_2020["Cash_ratio"].values.reshape(-1, 1)  # -1 means that calculate the dime

linear_regressor = LinearRegression()  # create object for the class
linear_regressor.fit(X, y)  # perform linear regression
Y_pred = linear_regressor.predict(X)  # make predictions

plt.figure(figsize=(10,5))
plt.scatter(X, y,color='mediumseagreen')
plt.plot(X, Y_pred, color='cornflowerblue')

plt.title('Tangibility and Cash ratio - UK', fontsize=18);
plt.xlabel('Tangibility', fontsize=13)
plt.ylabel('Cash ratio', fontsize=13)
plt.show()
```



Correlation analysis and heatmap of the correlation matrix

- We use the corr() method to calculate the correlation between the variables in our Australian sample.

In [63]:
```
CorrMatrix = df_au1.corr()
CorrMatrix
```

Out[63]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
Tangibility	1.000	-0.152	0.221	0.002	-0.259	0.020
Market_to_book	-0.152	1.000	-0.115	0.230	0.365	0.085
Log_TA	0.221	-0.115	1.000	0.116	-0.256	0.017
Profitability	0.002	0.230	0.116	1.000	0.072	-0.059
Cash_ratio	-0.259	0.365	-0.256	0.072	1.000	0.057
Year	0.020	0.085	0.017	-0.059	0.057	1.000

- We then use heatmap() from Seaborn to plot the correlation matrix.

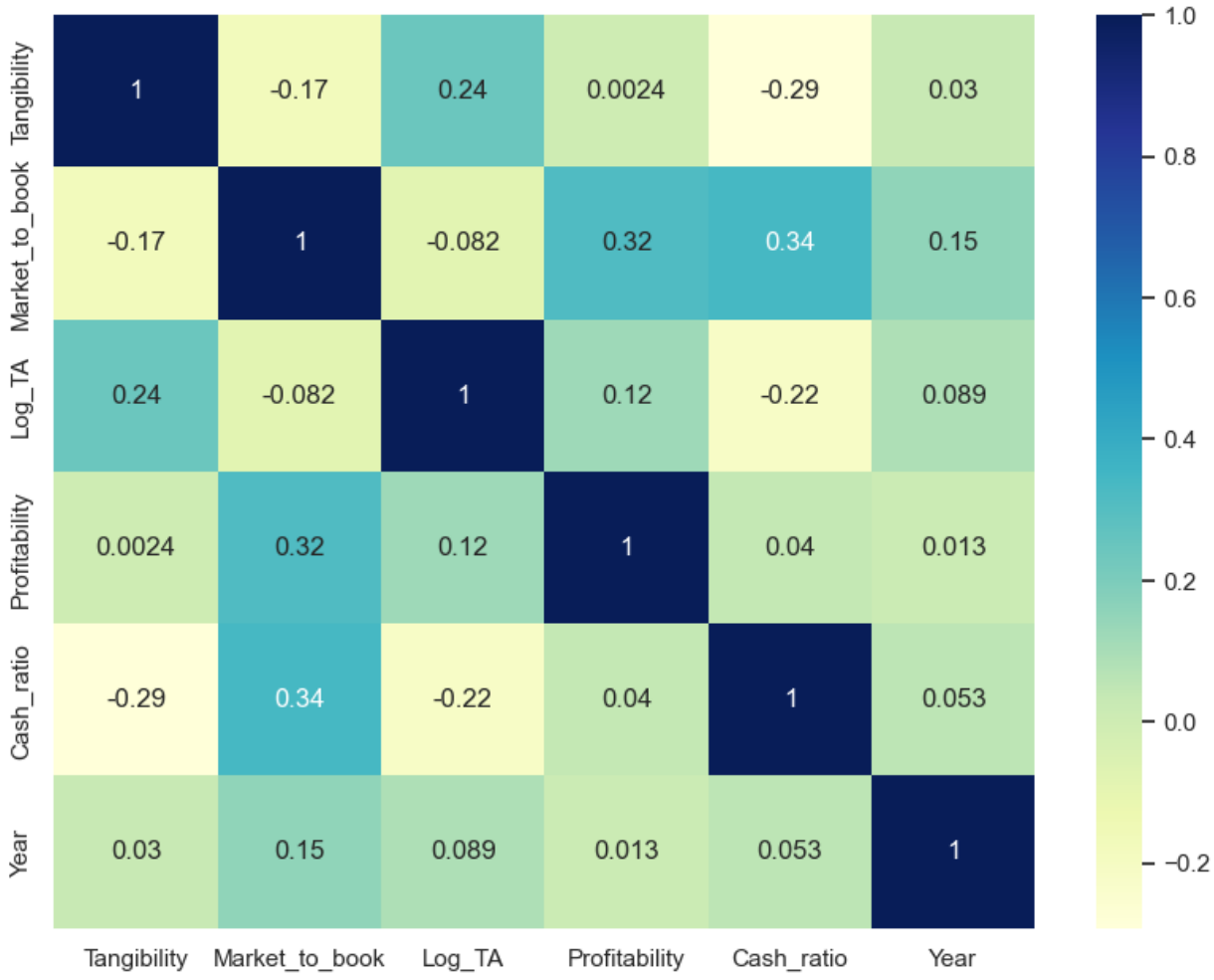
In [125…
```
CorrMatrix_uk = df_uk1.corr()
CorrMatrix_uk
```

Out[125]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
Tangibility	1.000	-0.175	0.243	0.002	-0.292	0.030
Market_to_book	-0.175	1.000	-0.082	0.317	0.342	0.152
Log_TA	0.243	-0.082	1.000	0.123	-0.216	0.089
Profitability	0.002	0.317	0.123	1.000	0.040	0.013
Cash_ratio	-0.292	0.342	-0.216	0.040	1.000	0.053
Year	0.030	0.152	0.089	0.013	0.053	1.000

In [64]:
```
plt.subplots(figsize=(10,7.5))
sns.heatmap(CorrMatrix,annot=True,cmap="YlGnBu")
plt.show()
```

In [126…
```
plt.subplots(figsize=(10,7.5))
sns.heatmap(CorrMatrix_uk,annot=True,cmap="YlGnBu")
plt.show()
```



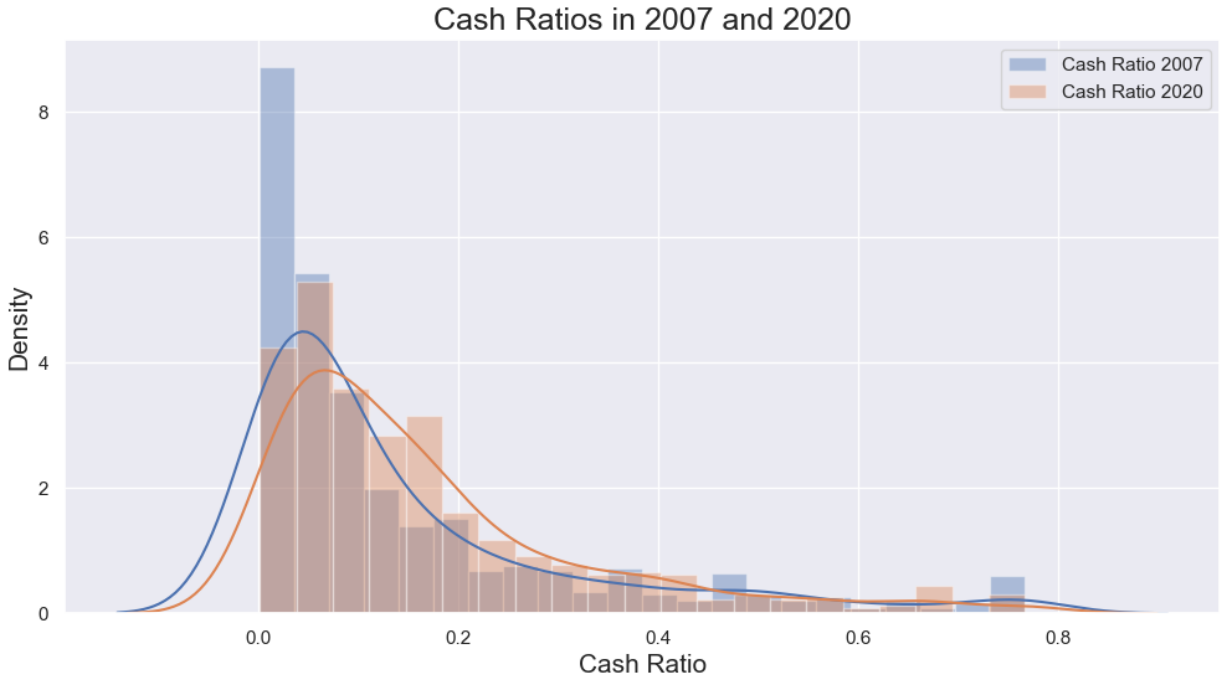
Kernet Density and Histogram Analysis

Compare the distribution of cash ratio in 2007 and 2020 using distplot()

In [128…

```
# Select the observations for 2007 and 2020
df_au_2007 = df_au1[df_au1['Year'] == 2007]
df_au_2020 = df_au1[df_au1['Year'] == 2020]

plt.figure(figsize=(12,6))
plt.xlabel('Cash Ratio', fontsize=15)
plt.ylabel('Density', fontsize=15)
plt.title("Cash Ratios in 2007 and 2020",fontsize=18)

sns.distplot(df_au_2007["Cash_ratio"].values, label="Cash Ratio 2007");
sns.distplot(df_au_2020["Cash_ratio"].values, label="Cash Ratio 2020");
plt.legend()
plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



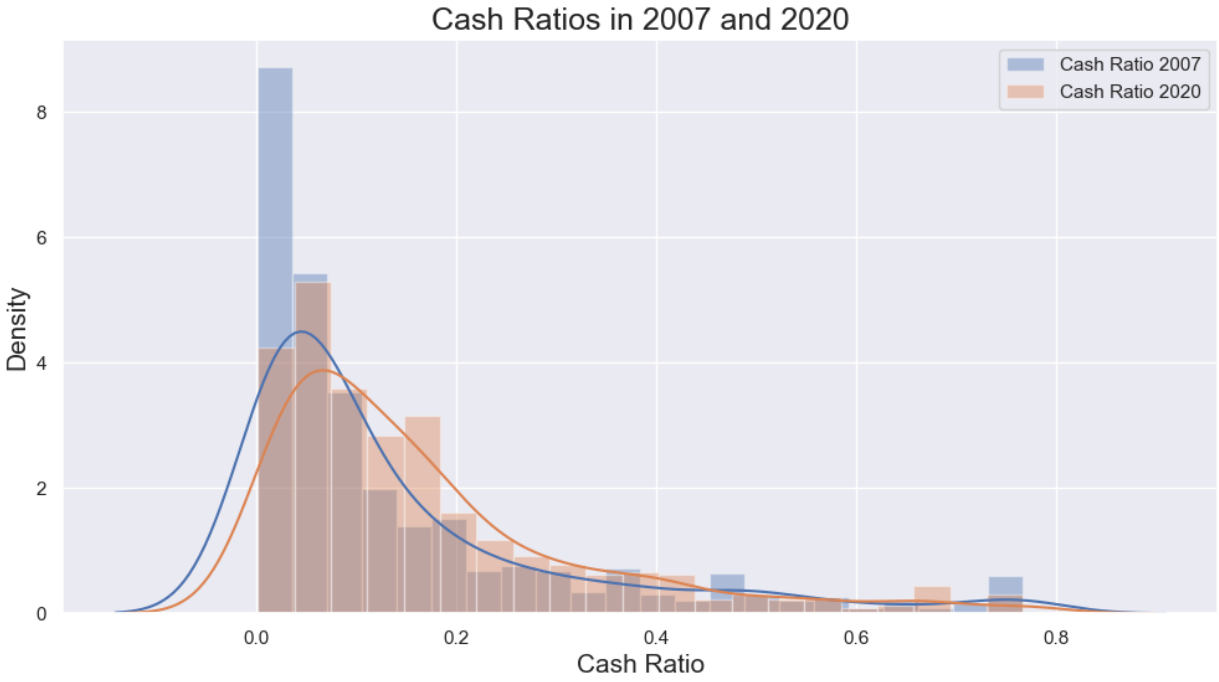
Interpretations:

- The figure above shows that the incidence of the lowest cash holding group has decreased substantially in 2020, comapred with 2007.
- On the other hand, for the other groups, cash holding are higher in 2020 than 2007.
- So companies are now less likely to hold very low level of debt and more likely to hold higher levels of cash.

In [127…

```
# Select the observations for 2007 and 2020
df_uk_2007 = df_uk1[df_uk1['Year'] == 2007]
df_uk_2020 = df_uk1[df_uk1['Year'] == 2020]

plt.figure(figsize=(12,6))
plt.xlabel('Cash Ratio', fontsize=15)
plt.ylabel('Density', fontsize=15)
plt.title("Cash Ratios in 2007 and 2020",fontsize=18)

sns.distplot(df_au_2007["Cash_ratio"].values, label="Cash Ratio 2007");
sns.distplot(df_au_2020["Cash_ratio"].values, label="Cash Ratio 2020");
plt.legend()
plt.show()
```

```
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
C:\Users\HP\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please a
dapt your code to use either `displot` (a figure-level function with similar flexibil
ity) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



Regression Analysis

We use the ordinary least squares or ols method from the statsmodels to look at the relation between firm characteristics

such as asset tangibility (Tangibility), market to book ratio (Market_to_book) and Cash to asset ratio.

$$Cash\_ratio = a + b\,Tangibility + c\,Market_to_book + d\,Log_TA + e\,Profitability$$

where: Cash_ratio is the dependent variable that we are trying to explain Tangibility, Market_to_book, Log_TA and Profitability are the explanatory variables or independent variables and 'a' is the Intercept of the model and 'b','c','d' and 'e' are the coefficients.

The coefiicients tell us about the relation between the independent variables and the dependent variable (Cash_ratio) For example, coefficient 'b' on Tangibility says that one unit increase in Tangibility ratio increases Cash_ratio by 'b'.

Now Let's estimate this regression on our data for Australia

In [130…
```
import statsmodels.formula.api as sm

result_aus = sm.ols(formula="Cash_ratio ~ Tangibility + Market_to_book + Log_TA + Prof
print(result_aus.params)
```

```
Intercept         0.202
Tangibility      -0.099
Market_to_book    0.036
Log_TA           -0.016
Profitability     0.019
dtype: float64
```

In [131…
```
result_uk = sm.ols(formula="Cash_ratio ~ Tangibility + Market_to_book + Log_TA + Profi
print(result_uk.params)
```

```
Intercept         0.174
Tangibility      -0.116
Market_to_book    0.037
Log_TA           -0.011
Profitability    -0.040
dtype: float64
```

The output above shows the estimated coefficients of the model given above. So we have:

a = 0.197 b = -0.094 c = 0.035 d = -0.016 e = 0.026

Thus if Tangibility ratio increases by 50% or 0.5, then Cash ratio is predicted to decrease by 0.5* (-0.094) = -0.047 or 4.7%

We can get the full results as follows:

In [132…
```
print(result_aus.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Cash_ratio   R-squared:                       0.207
Model:                            OLS   Adj. R-squared:                  0.207
Method:                 Least Squares   F-statistic:                     670.4
Date:                Thu, 23 Feb 2023   Prob (F-statistic):               0.00
Time:                        21:36:30   Log-Likelihood:                 5466.7
No. Observations:               10278   AIC:                        -1.092e+04
Df Residuals:                   10273   BIC:                        -1.089e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                     coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept          0.2019      0.005     39.900      0.000       0.192       0.212
Tangibility       -0.0988      0.005    -18.793      0.000      -0.109      -0.089
Market_to_book     0.0357      0.001     33.955      0.000       0.034       0.038
Log_TA            -0.0164      0.001    -20.188      0.000      -0.018      -0.015
Profitability      0.0189      0.008      2.429      0.015       0.004       0.034
==============================================================================
Omnibus:                     3194.048   Durbin-Watson:                   0.793
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             9680.540
Skew:                           1.617   Prob(JB):                         0.00
Kurtosis:                       6.485   Cond. No.                         33.7
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
```

Here we get the coefficients under the coef column, which are the same as before. But we also get the statistical significance, or the P-values, of the coefficients under th P>|t| column.

In this case the P-values are all less than 0.01, so all the variables have a significat relation with Cash_ratio at the 1% level, which means the relations are highly significant.

In [133…

```
print(result_uk.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Cash_ratio   R-squared:                       0.193
Model:                            OLS   Adj. R-squared:                  0.192
Method:                 Least Squares   F-statistic:                     868.5
Date:                Thu, 23 Feb 2023   Prob (F-statistic):               0.00
Time:                        21:36:47   Log-Likelihood:                 8411.7
No. Observations:               14568   AIC:                        -1.681e+04
Df Residuals:                   14563   BIC:                        -1.678e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept      0.1741      0.004     43.177      0.000       0.166       0.182
Tangibility   -0.1163      0.004    -26.376      0.000      -0.125      -0.108
Market_to_book 0.0369      0.001     38.312      0.000       0.035       0.039
Log_TA        -0.0107      0.001    -17.482      0.000      -0.012      -0.009
Profitability -0.0404      0.008     -5.006      0.000      -0.056      -0.025
==============================================================================
Omnibus:                     4879.425   Durbin-Watson:                   0.692
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            16700.141
Skew:                           1.697   Prob(JB):                         0.00
Kurtosis:                       6.999   Cond. No.                         45.8
==============================================================================

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is correctly spec
ified.
```

Correlation Analysis

Now Let's estimate the correlation coefficients and the p-values for the Australia sample

We use the stats.pearsonr() function to calculate the correlation matrix for our variables of interest.

In [134…

```
from scipy import stats

df_corr = pd.DataFrame()
df_corr_p = pd.DataFrame()

for x in df_au1.columns:
    for y in df_au1.columns:
        corr_result = stats.pearsonr(df_au1[x], df_au1[y])
        df_corr.loc[x,y] = corr_result[0]
        df_corr_p.loc[x,y] = corr_result[1]
```

In [135…

```
# Display the correlation coefficients
df_corr
```

Out[135]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
Tangibility	1.000	-0.152	0.221	0.002	-0.259	0.020
Market_to_book	-0.152	1.000	-0.115	0.230	0.365	0.085
Log_TA	0.221	-0.115	1.000	0.116	-0.256	0.017
Profitability	0.002	0.230	0.116	1.000	0.072	-0.059
Cash_ratio	-0.259	0.365	-0.256	0.072	1.000	0.057
Year	0.020	0.085	0.017	-0.059	0.057	1.000

In [136…

```
# Display the correlation p-values
df_corr_p
```

Out[136]:

	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio	Year
Tangibility	0.000	0.000	0.000	0.824	0.000	0.041
Market_to_book	0.000	0.000	0.000	0.000	0.000	0.000
Log_TA	0.000	0.000	0.000	0.000	0.000	0.081
Profitability	0.824	0.000	0.000	0.000	0.000	0.000
Cash_ratio	0.000	0.000	0.000	0.000	0.000	0.000
Year	0.041	0.000	0.081	0.000	0.000	0.000

Compare cash ratio across countries over the years

In [137…

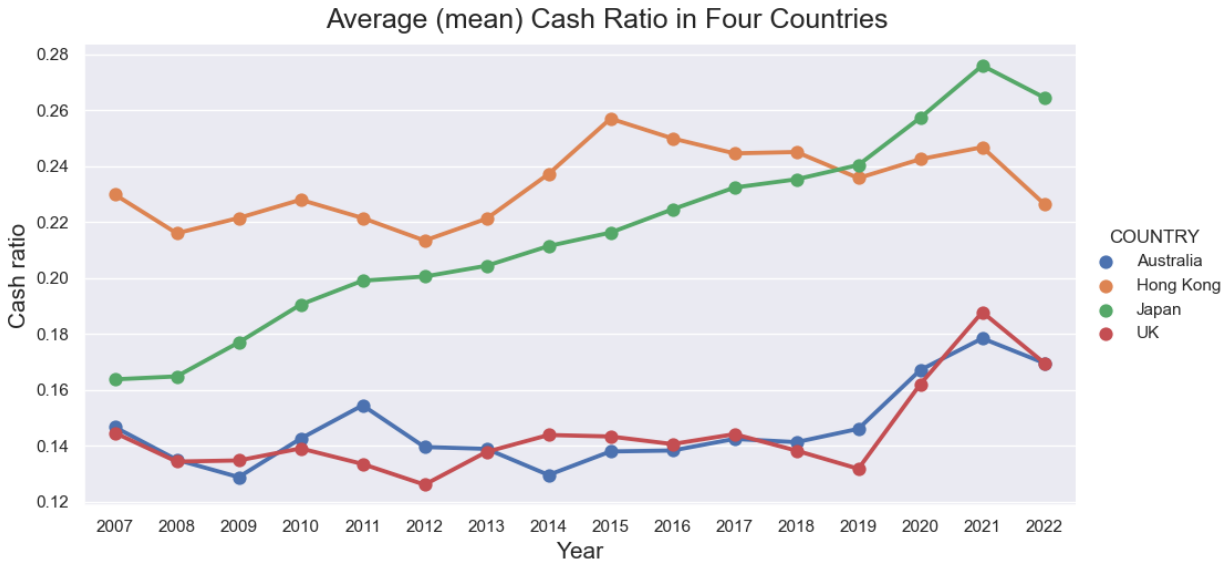
```
df41=df3.groupby(['COUNTRY', 'Year']).mean()

df_flat1 = df41.reset_index()

df_flat1.head()
```

Out[137]:

	COUNTRY	Year	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio
0	Australia	2007	0.283	2.208	5.333	0.133	0.147
1	Australia	2008	0.276	1.558	5.392	0.073	0.135
2	Australia	2009	0.295	1.314	5.351	0.057	0.129
3	Australia	2010	0.273	1.414	5.394	0.091	0.143
4	Australia	2011	0.266	1.458	5.531	0.079	0.155

In [138…

```
ax = sns.catplot(x="Year", y="Cash_ratio", hue="COUNTRY", kind="point", data=df_flat1,
    aspect=2); # height should be three times width

ax.fig.suptitle('Average (mean) Cash Ratio in Four Countries',fontsize=18,y=1.03);
plt.xlabel('Year', fontsize=15);
plt.ylabel('Cash ratio', fontsize=15);
```



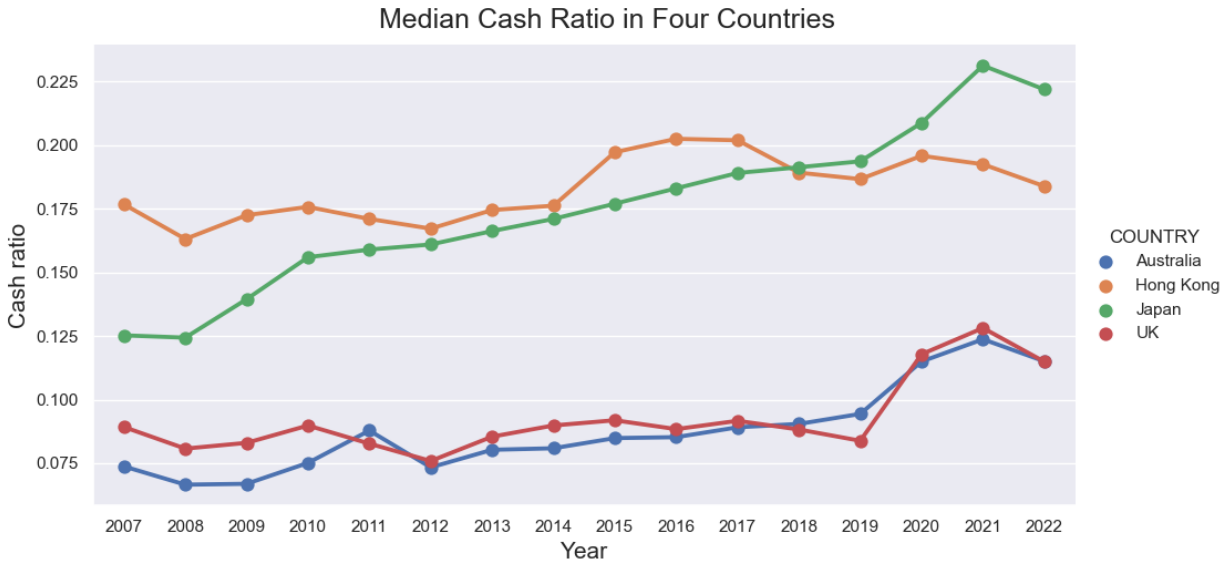
In [139…
```
plt.figure(figsize=(20,10))
df42=df3.groupby(['COUNTRY', 'Year']).median()

df_flat2 = df42.reset_index()
df_flat2.head()
```

Out[139]:

	COUNTRY	Year	Tangibility	Market_to_book	Log_TA	Profitability	Cash_ratio
0	Australia	2007	0.194	1.496	5.075	0.125	0.074
1	Australia	2008	0.178	1.120	5.150	0.105	0.067
2	Australia	2009	0.206	0.999	5.090	0.094	0.067
3	Australia	2010	0.169	1.097	5.160	0.098	0.075
4	Australia	2011	0.156	1.053	5.299	0.092	0.088

```
<Figure size 2000x1000 with 0 Axes>
```

In [140…
```
ax = sns.catplot(x="Year", y="Cash_ratio", hue="COUNTRY", kind="point", data=df_flat2,
    aspect=2); # height should be three times width);

ax.fig.suptitle('Median Cash Ratio in Four Countries',fontsize=18,y=1.03);
plt.xlabel('Year', fontsize=15);
plt.ylabel('Cash ratio', fontsize=15);
```


Median Cash Ratio in Four Countries
Cash ratio
0.225
0.200
0.175
0.150
0.125
0.100
0.075
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
Year
COUNTRY
Australia
Hong Kong
Japan
UK