Could not connect to the reCAPTCHA service. Please check your internet connection and reload to get a reCAPTCHA challenge.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)

# Suppress only RuntimeWarnings
warnings.filterwarnings("ignore", category=RuntimeWarning)
```

```
!gdown '15_3e9du3eRDWGEOG2jwYJ1rumoxgkoct'
```

```
Downloading...
From: https://drive.google.com/uc?id=15_3e9du3eRDWGEOG2jwYJ1rumoxgkoct
To: /content/Investments_VC_colab.csv
100% 12.5M/12.5M [00:00<00:00, 37.3MB/s]
```

```
df = pd.read_csv('/content/Investments_VC_colab.csv',encoding='latin-1')
df.head(10)
```

	permalink	name	homepage_url	category_list	market	funding_tota
0	/organization/waywire	#waywire	http://www.waywire.com	|Entertainment|Politics|Social Media|News|	News	17,!
1	/organization/tv-communications	&TV Communications	http://enjoyandtv.com	|Games|	Games	40,(
2	/organization/rock-your-paper	'Rock' Your Paper	http://www.rockyourpaper.org	|Publishing|Education|	Publishing	‹
3	/organization/in-touch-network	(In)Touch Network	http://www.InTouchNetwork.com	|Electronics|Guides|Coffee|Restaurants|Music|i...	Electronics	15,(
4	/organization/r-ranch-and-mine	-R- Ranch and Mine	NaN	|Tourism|Entertainment|Games|	Tourism	(
5	/organization/club-domains	.Club Domains	http://nic.club/	|Software|	Software	70,(
6	/organization/fox-networks	.Fox Networks	http://www.dotfox.com	|Advertising|	Advertising	49,'
7	/organization/0-6-com	0-6.com	http://www.0-6.com	|Curated Web|	Curated Web	20,(
8	/organization/004-technologies	004 Technologies	http://004gmbh.de/en/004-interact	|Software|	Software	
9	/organization/01games-technology	01Games Technology	http://www.01games.hk/	|Games|	Games	‹

Basic EDA

```
df.duplicated().sum()
```

```
4855
```

```
df = df.dropna(how='all')
```

```
df = df.drop_duplicates()
```

```
df.shape
```

```
(49438, 39)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 49438 entries, 0 to 49437
Data columns (total 39 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   permalink             49438 non-null  object
 1   name                  49437 non-null  object
```

```
 2   homepage_url          45989 non-null  object 
 3   category_list         45477 non-null  object 
 4    market               45470 non-null  object 
 5    funding_total_usd    49438 non-null  object 
 6   status                48124 non-null  object 
 7   country_code          44165 non-null  object 
 8   state_code            30161 non-null  object 
 9   region                44165 non-null  object 
 10  city                  43322 non-null  object 
 11  funding_rounds        49438 non-null  float64
 12  founded_at            38554 non-null  object 
 13  founded_month         38482 non-null  object 
 14  founded_quarter       38482 non-null  object 
 15  founded_year          38482 non-null  float64
 16  first_funding_at      49438 non-null  object 
 17  last_funding_at       49438 non-null  object 
 18  seed                  49438 non-null  float64
 19  venture               49438 non-null  float64
 20  equity_crowdfunding   49438 non-null  float64
 21  undisclosed           49438 non-null  float64
 22  convertible_note      49438 non-null  float64
 23  debt_financing        49438 non-null  float64
 24  angel                 49438 non-null  float64
 25  grant                 49438 non-null  float64
 26  private_equity        49438 non-null  float64
 27  post_ipo_equity       49438 non-null  float64
 28  post_ipo_debt         49438 non-null  float64
 29  secondary_market      49438 non-null  float64
 30  product_crowdfunding  49438 non-null  float64
 31  round_A               49438 non-null  float64
 32  round_B               49438 non-null  float64
 33  round_C               49438 non-null  float64
 34  round_D               49438 non-null  float64
 35  round_E               49438 non-null  float64
 36  round_F               49438 non-null  float64
 37  round_G               49438 non-null  float64
 38  round_H               49438 non-null  float64
dtypes: float64(23), object(16)
memory usage: 15.1+ MB
```

```
# Checking number of empty values in each column
df.isna().sum()/len(df)*100
```

	0
permalink	0.000000
name	0.002023
homepage_url	6.976415
category_list	8.012056
market	8.026215
funding_total_usd	0.000000
status	2.657875
country_code	10.665885
state_code	38.992273
region	10.665885
city	12.371051
funding_rounds	0.000000
founded_at	22.015454
founded_month	22.161091
founded_quarter	22.161091
founded_year	22.161091
first_funding_at	0.000000
last_funding_at	0.000000
seed	0.000000
venture	0.000000
equity_crowdfunding	0.000000
undisclosed	0.000000
convertible_note	0.000000
debt_financing	0.000000
angel	0.000000
grant	0.000000
private_equity	0.000000
post_ipo_equity	0.000000
post_ipo_debt	0.000000
secondary_market	0.000000
product_crowdfunding	0.000000
round_A	0.000000
round_B	0.000000
round_C	0.000000
round_D	0.000000
round_E	0.000000
round_F	0.000000
round_G	0.000000
round_H	0.000000

```
df.describe().T
```

	count	mean	std	min	25%	50%	75%	max
funding_rounds	49438.0	1.696205e+00	1.294213e+00	1.0	1.0	1.0	2.0	1.800000e+01
founded_year	38482.0	2.007359e+03	7.579203e+00	1902.0	2006.0	2010.0	2012.0	2.014000e+03
seed	49438.0	2.173215e+05	1.056985e+06	0.0	0.0	0.0	25000.0	1.300000e+08
venture	49438.0	7.501051e+06	2.847112e+07	0.0	0.0	0.0	5000000.0	2.351000e+09
equity_crowdfunding	49438.0	6.163322e+03	1.999048e+05	0.0	0.0	0.0	0.0	2.500000e+07
undisclosed	49438.0	1.302213e+05	2.981404e+06	0.0	0.0	0.0	0.0	2.924328e+08
convertible_note	49438.0	2.336410e+04	1.432046e+06	0.0	0.0	0.0	0.0	3.000000e+08
debt_financing	49438.0	1.888157e+06	1.382046e+08	0.0	0.0	0.0	0.0	3.007950e+10
angel	49438.0	6.541898e+04	6.582908e+05	0.0	0.0	0.0	0.0	6.359026e+07
grant	49438.0	1.628453e+05	5.612088e+06	0.0	0.0	0.0	0.0	7.505000e+08
private_equity	49438.0	2.074286e+06	3.167231e+07	0.0	0.0	0.0	0.0	3.500000e+09
post_ipo_equity	49438.0	6.088736e+05	2.678348e+07	0.0	0.0	0.0	0.0	4.700000e+09
post_ipo_debt	49438.0	4.434360e+05	3.428169e+07	0.0	0.0	0.0	0.0	5.800000e+09
secondary_market	49438.0	3.845592e+04	3.864461e+06	0.0	0.0	0.0	0.0	6.806116e+08
product_crowdfunding	49438.0	7.074227e+03	4.282166e+05	0.0	0.0	0.0	0.0	7.200000e+07
round_A	49438.0	1.243955e+06	5.531974e+06	0.0	0.0	0.0	0.0	3.190000e+08
round_B	49438.0	1.492891e+06	7.472704e+06	0.0	0.0	0.0	0.0	5.420000e+08
round_C	49438.0	1.205356e+06	7.993592e+06	0.0	0.0	0.0	0.0	4.900000e+08
round_D	49438.0	7.375261e+05	9.815218e+06	0.0	0.0	0.0	0.0	1.200000e+09
round_E	49438.0	3.424682e+05	5.406915e+06	0.0	0.0	0.0	0.0	4.000000e+08
round_F	49438.0	1.697692e+05	6.277905e+06	0.0	0.0	0.0	0.0	1.060000e+09
round_G	49438.0	5.767067e+04	5.252312e+06	0.0	0.0	0.0	0.0	1.000000e+09
round_H	49438.0	1.423197e+04	2.716865e+06	0.0	0.0	0.0	0.0	6.000000e+08

```
df.describe(exclude=np.number).T
```

	count	unique	top	freq
permalink	49438	49436	/organization/treasure-valley-urology-services	2
name	49437	49350	Roost	4
homepage_url	45989	45850	http://spaceport.io	2
category_list	45477	16675	|Software|	3650
market	45470	753	Software	4620
funding_total_usd	49438	14617	-	8531
status	48124	3	operating	41829
country_code	44165	115	USA	28793
state_code	30161	61	CA	9917
region	44165	1089	SF Bay Area	6804
city	43322	4188	San Francisco	2615
founded_at	38554	3369	2012-01-01	2181
founded_month	38482	420	2012-01	2327
founded_quarter	38482	218	2012-Q1	2904
first_funding_at	49438	3914	2012-01-01	468
last_funding_at	49438	3657	2013-01-01	387

Observations :

1. There are total 49436 unique permalink.
2. There are 49350 unique names of the startup in the dataset.
3. There are 753 unique market listed in the dataset.
4. There are 1089 unique regions mentioned in the dataset.

5. The dataset needs data cleaning as we can see the there are hyphens(garbage value) present in the columns.

Helper Function

```
# Function to print basic useful details for a given column
def get_column_details(df,column):
    print("Details of",column,"column")

    #DataType of column
    print("\nDataType: ",df[column].dtype)

    #Check if null values are present
    count_null = df[column].isnull().sum()
    if count_null==0:
        print("\nThere are no null values")
    elif count_null>0:
        print("\nThere are ",count_null," null values")

    #Get Number of Unique Values
    print("\nNumber of Unique Values: ",df[column].nunique())

    #Get Distribution of Column
    print("\nDistribution of column:\n")
    print(df[column].value_counts())
```

Objective Variables

```
# permalink
get_column_details(df,'permalink')
```

```
Details of permalink column

DataType:  object

There are no null values

Number of Unique Values:  49436

Distribution of column:

permalink
/organization/treasure-valley-urology-services    2
/organization/prysm                               2
/organization/waywire                             1
/organization/polybona                            1
/organization/pollfish                            1
                                                 ..
/organization/game-ventures                       1
/organization/game9z                              1
/organization/gameaccount-network                 1
/organization/gameanalytics                       1
/organization/x                                   1
Name: count, Length: 49436, dtype: int64
```

```
# name
get_column_details(df,'name')
```

```
Details of name column

DataType:  object

There are  1  null values

Number of Unique Values:  49350

Distribution of column:

name
Roost                 4
Spire                 4
Cue                   3
Compass               3
Hubbub                3
                     ..
Game Trust            1
Game Ventures         1
Game9z                1
GameAccount Network   1
[x+1]                 1
```

```
Name: count, Length: 49350, dtype: int64
```

```
# cleaning
# Step 1: Assign 'None' to np.NaN
df['name'] = df['name'].replace([None], np.NaN)
print("\nGarbage value 'None' is replaced with np.nan")

# Step 2: Fill missing 'name' values based on 'permalink'
df['name'] = df.apply(
    lambda row: row['permalink'].split('/')[-1].capitalize() if pd.isna(row['name']) else row['name'],
    axis=1
)

print("\nMissing values in 'name' column are filled using 'permalink'")
```

```
Garbage value 'None' is replaced with np.nan

Missing values in 'name' column are filled using 'permalink'
```

```
get_column_details(df,'name')
```

```
Details of name column

DataType:  object

There are no null values

Number of Unique Values:  49351

Distribution of column:

name
Roost                 4
Spire                 4
Cue                   3
Compass               3
Hubbub                3
                     ..
Game Trust            1
Game Ventures         1
Game9z                1
GameAccount Network   1
[x+1]                 1
Name: count, Length: 49351, dtype: int64
```

```
get_column_details(df,'homepage_url')
```

```
Details of homepage_url column

DataType:  object

There are  3449  null values

Number of Unique Values:  45850

Distribution of column:

homepage_url
http://spaceport.io               2
http://shelby.tv                  2
http://www.kuwo.cn                2
http://gui.de                     2
http://primordialgenetics.com     2
                                 ..
http://www.gamecooks.net          1
http://www.game-craft.com         1
http://www.gamedigitalplc.com     1
http://game-insight.com           1
http://www.xplusone.com/          1
Name: count, Length: 45850, dtype: int64
```

```
df['homepage_url'] = df['homepage_url'].fillna("Not Available")
```

```
get_column_details(df,'homepage_url')
```

```
Details of homepage_url column

DataType:  object

There are no null values

Number of Unique Values:  45851
```

```
Distribution of column:

homepage_url
Not Available                   3449
http://spaceport.io                2
http://ivillage.com                2
http://www.kuwo.cn                 2
http://gui.de                      2
                                ...
http://www.gamecooks.net           1
http://www.game-craft.com          1
http://www.gamedigitalplc.com      1
http://game-insight.com            1
http://www.xplusone.com/           1
Name: count, Length: 45851, dtype: int64
```

```
# category list
get_column_details(df,'category_list')
```

```
Details of category_list column

DataType:  object

There are  3961  null values

Number of Unique Values:  16675

Distribution of column:

category_list
|Software|                                                                                    3650
|Biotechnology|                                                                               3597
|E-Commerce|                                                                                  1263
|Mobile|                                                                                      1211
|Curated Web|                                                                                 1120
                                                                                              ...
|Fashion|Digital Media|Marketplaces|E-Commerce|                                                  1
|Advertising|Web Development|App Marketing|Enterprises|Cloud Computing|Enterprise Software|      1
|Web Design|Software|Web Tools|Web Development|Enterprise Software|                              1
|3D|Web Tools|Entertainment|Curated Web|                                                         1
|Web Development|Advertising|Wireless|Mobile|                                                    1
Name: count, Length: 16675, dtype: int64
```

```
df['category_list'] = df['category_list'].fillna("Not Listed")
```

```
get_column_details(df,'category_list')
```

```
Details of category_list column

DataType:  object

There are no null values

Number of Unique Values:  16676

Distribution of column:

category_list
Not Listed                                                                                    3961
|Software|                                                                                    3650
|Biotechnology|                                                                               3597
|E-Commerce|                                                                                  1263
|Mobile|                                                                                      1211
                                                                                              ...
|Fashion|Digital Media|Marketplaces|E-Commerce|                                                  1
|Advertising|Web Development|App Marketing|Enterprises|Cloud Computing|Enterprise Software|      1
|Web Design|Software|Web Tools|Web Development|Enterprise Software|                              1
|3D|Web Tools|Entertainment|Curated Web|                                                         1
|Web Development|Advertising|Wireless|Mobile|                                                    1
Name: count, Length: 16676, dtype: int64
```

```
get_column_details(df,' market ')
```

```
Details of  market  column

DataType:  object

There are  3968  null values

Number of Unique Values:  753

Distribution of column:

 market
Software                 4620
```

```
Biotechnology           3688
Mobile                  1983
E-Commerce              1805
Curated Web             1655
                        ...
Contact Centers            1
Swimming                   1
Retirement                 1
Musical Instruments        1
Rural Energy               1
Name: count, Length: 753, dtype: int64
```

```
df[' market '] = df[' market '].fillna("Not Listed")
```

```
get_column_details(df,' market ')
```

```
Details of  market  column

DataType:  object

There are no null values

Number of Unique Values:  754

Distribution of column:

 market
 Software                4620
Not Listed               3968
 Biotechnology           3688
 Mobile                  1983
 E-Commerce              1805
                         ...
 Contact Centers            1
 Swimming                   1
 Retirement                 1
 Musical Instruments        1
 Rural Energy               1
Name: count, Length: 754, dtype: int64
```

```
get_column_details(df,' funding_total_usd ')
```

```
Details of  funding_total_usd  column

DataType:  object

There are no null values

Number of Unique Values:  14617

Distribution of column:

 funding_total_usd
-               8531
10,00,000        925
5,00,000         761
1,00,000         749
40,000           680
                ...
1,79,26,365        1
1,77,404           1
2,52,052           1
2,15,563           1
97,398             1
Name: count, Length: 14617, dtype: int64
```

```
# Replace commas with empty strings
df[' funding_total_usd '] = df[' funding_total_usd '].str.replace(',', '', regex=True)

# Convert to numeric if needed
df[' funding_total_usd '] = pd.to_numeric(df[' funding_total_usd '], errors='coerce')
```

```
df[' funding_total_usd '] = df[' funding_total_usd '].fillna(0)
```

```
get_column_details(df,' funding_total_usd ')
```

```
Details of  funding_total_usd  column

DataType:  float64

There are no null values

Number of Unique Values:  14617
```

```
Distribution of column:

 funding_total_usd
0.0           8531
1000000.0      925
500000.0       761
100000.0       749
40000.0        680
              ...
17926365.0       1
177404.0         1
252052.0         1
215563.0         1
97398.0          1
Name: count, Length: 14617, dtype: int64
```

```
get_column_details(df,'status')
```

```
Details of status column

DataType:  object

There are  1314  null values

Number of Unique Values:  3

Distribution of column:

status
operating    41829
acquired      3692
closed        2603
Name: count, dtype: int64
```

```
df['status'] = df['status'].fillna("Not Available")
```

```
get_column_details(df,'status')
```

```
Details of status column

DataType:  object

There are no null values

Number of Unique Values:  4

Distribution of column:

status
operating        41829
acquired          3692
closed            2603
Not Available     1314
Name: count, dtype: int64
```

```
# Update the specified columns to "Not Available"
df['country_code'] = df['country_code'].fillna('Not Available')
df['state_code'] = df['state_code'].fillna('Not Available')
df['region'] = df['region'].fillna('Not Available')
df['city'] = df['city'].fillna('Not Available')
```

```
get_column_details(df,'country_code')
```

```
BHR                 3
BLR                 3
AZE                 3
TUN                 3
SLV                 3
DOM                 3
MLT                 3
GIB                 2
MKD                 2
KWT                 2
MMR                 2
NIC                 2
ECU                 2
MDA                 2
NPL                 2
BHS                 2
CMR                 2
LAO                 2
ARM                 2
TTO                 1
JAM                 1
SYC                 1
SOM                 1
CIV                 1
MUS                 1
OMN                 1
JEY                 1
UZB                 1
ZWE                 1
MCO                 1
ALB                 1
MOZ                 1
LIE                 1
BRN                 1
MAF                 1
Name: count, dtype: int64
```

```
get_column_details(df,'state_code')
```

```
WA                974
FL                963
IL                827
PA                792
CO                723
ON                653
NJ                579
VA                553
GA                541
OH                532
MD                493
NC                476
TN                411
UT                365
MN                355
AZ                327
BC                318
CT                316
MI                313
OR                312
IN                233
MO                220
QC                219
NV                195
WI                191
DC                182
AR                177
SC                125
AB                115
KY                113
NH                112
AL                105
RI                104
KS                 94
IA                 78
```

```
SD                  14
MB                  13
AK                  12
NB                   8
SK                   4
PE                   2
Name: count, dtype: int64
```

```
get_column_details(df,'region')
```

```
Details of region column

DataType:  object

There are no null values

Number of Unique Values:  1090

Distribution of column:

region
SF Bay Area        6804
Not Available      5273
New York City      2577
Boston             1837
London             1588
                   ...
Palma Del Río         1
Harbin                1
Teddington            1
Borehamwood           1
Buckinghamshire       1
Name: count, Length: 1090, dtype: int64
```

```
get_column_details(df,'city')
```

```
Details of city column

DataType:  object

There are no null values

Number of Unique Values:  4189

Distribution of column:

city
Not Available            6116
San Francisco            2615
New York                 2334
London                   1257
Palo Alto                 597
                          ...
Pekin                       1
Fort Ripley                 1
Chelyabinsk-40              1
Yavneh                      1
Damansara New Village       1
Name: count, Length: 4189, dtype: int64
```

```
get_column_details(df,'funding_rounds')
```

```
Details of funding_rounds column

DataType:  float64

There are no null values

Number of Unique Values:  17

Distribution of column:

funding_rounds
1.0     32039
2.0      9219
3.0      4026
4.0      1997
5.0      1001
6.0       560
7.0       252
8.0       152
9.0        84
10.0       43
11.0       35
12.0       12
13.0        8
15.0        4
14.0        4
```

```
16.0        1
18.0        1
Name: count, dtype: int64
```

```
df['founded_at'] = pd.to_datetime(df['founded_at'], errors='coerce')
```

```
get_column_details(df,'founded_at')
```

```
Details of founded_at column

DataType:  datetime64[ns]

There are  10885  null values

Number of Unique Values:  3368

Distribution of column:

founded_at
2012-01-01    2181
2011-01-01    2161
2010-01-01    1855
2009-01-01    1603
2013-01-01    1575
              ...
2006-06-19       1
2002-11-20       1
2008-08-26       1
2003-05-29       1
2012-05-13       1
Name: count, Length: 3368, dtype: int64
```

```
df['founded_at'] = df['founded_at'].fillna('Not Available')
df['founded_month'] = df['founded_month'].fillna('Not Available')
df['founded_quarter'] = df['founded_quarter'].fillna('Not Available')
df['founded_year'] = df['founded_year'].fillna('Not Available')
```

```
get_column_details(df,'founded_at')
```

```
Details of founded_at column

DataType:  object

There are no null values

Number of Unique Values:  3369

Distribution of column:

founded_at
Not Available          10885
2012-01-01 00:00:00     2181
2011-01-01 00:00:00     2161
2010-01-01 00:00:00     1855
2009-01-01 00:00:00     1603
                        ...
2009-09-22 00:00:00        1
2009-05-24 00:00:00        1
1983-12-31 00:00:00        1
2009-02-19 00:00:00        1
2012-05-13 00:00:00        1
Name: count, Length: 3369, dtype: int64
```

```
get_column_details(df,'founded_month')
```

```
1969-09            1
1991-12            1
1983-11            1
1982-08            1
1994-03            1
1921-03            1
1970-06            1
1986-07            1
1986-12            1
1995-07            1
1995-04            1
1990-04            1
1997-11            1
1990-12            1
1986-04            1
1974-02            1
1963-09            1
1984-08            1
1991-08            1
1979-05            1
1969-03            1
1986-02            1
1918-01            1
1946-01            1
1984-09            1
1941-03            1
1905-01            1
1921-01            1
1994-09            1
1984-02            1
1986-06            1
1983-12            1
1974-03            1
1984-05            1
1929-01            1
1987-07            1
1994-10            1
Name: count, dtype: int64
```

```
get_column_details(df,'founded_quarter')
```

```
1941-Q1          1
1944-Q1          1
1962-Q1          1
1981-Q3          1
1991-Q3          1
1986-Q4          1
1960-Q2          1
1907-Q1          1
Name: count, dtype: int64
```

```
get_column_details(df,'founded_year')
```

```
1968.0          10
1960.0           9
1963.0           8
1966.0           8
1970.0           8
1961.0           8
1948.0           7
1912.0           6
1959.0           6
1924.0           6
1964.0           6
1954.0           5
1906.0           5
1952.0           5
1930.0           5
1922.0           4
1955.0           4
1928.0           4
1947.0           4
1965.0           3
1945.0           3
1919.0           3
1934.0           3
1958.0           3
1956.0           3
1949.0           2
1937.0           2
1950.0           2
1951.0           2
1910.0           2
1957.0           2
1921.0           2
1902.0           2
1911.0           2
1926.0           2
1962.0           2
1923.0           2
1914.0           2
1933.0           2
1913.0           2
1953.0           2
1939.0           1
1908.0           1
1903.0           1
1936.0           1
1938.0           1
1917.0           1
1925.0           1
1920.0           1
1941.0           1
1905.0           1
1929.0           1
1943.0           1
1946.0           1
1918.0           1
1944.0           1
1907.0           1
Name: count, dtype: int64
```

```
df['first_funding_at'] = pd.to_datetime(df['first_funding_at'], errors='coerce')
df['last_funding_at'] = pd.to_datetime(df['last_funding_at'], errors='coerce')
```

```
df['first_funding_at'] = df['first_funding_at'].fillna('Not Available')
df['last_funding_at'] = df['last_funding_at'].fillna('Not Available')
```

```
get_column_details(df,'first_funding_at')
```

```
Details of first_funding_at column

DataType:  object

There are no null values

Number of Unique Values:  3905
```

```
Distribution of column:

first_funding_at
2012-01-01    468
2013-01-01    463
2008-01-01    422
2011-01-01    392
2007-01-01    342
             ...
1999-08-31      1
2013-12-07      1
2004-08-25      1
2003-12-12      1
2004-10-12      1
Name: count, Length: 3905, dtype: int64
```

```
get_column_details(df,'last_funding_at')
```

```
Details of last_funding_at column

DataType:  object

There are no null values

Number of Unique Values:  3652

Distribution of column:

last_funding_at
2013-01-01    387
2014-01-01    364
2012-01-01    348
2008-01-01    302
2011-01-01    272
             ...
2005-05-14      1
2005-09-03      1
1986-07-03      1
2009-05-24      1
2008-07-13      1
Name: count, Length: 3652, dtype: int64
```

```
cols = ['seed','venture','equity_crowdfunding','undisclosed','convertible_note','debt_financing','angel', 'grant', 'private_equity', 'p
for col in cols:
    get_column_details(df,col)
```

```
Details of round_H column

DataType:  float64

There are no null values

Number of Unique Values:  5

Distribution of column:

round_H
0.0            49434
50000000.0         1
600000000.0        1
49000000.0         1
4600000.0          1
Name: count, dtype: int64
```

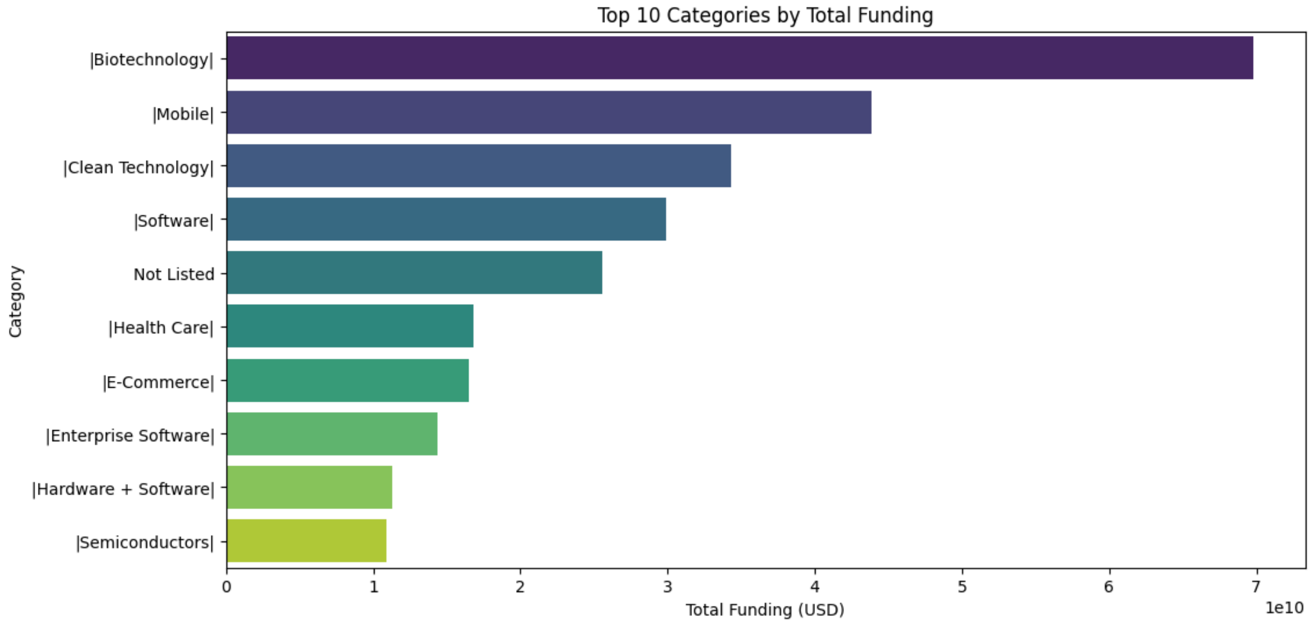
Feature Engineering

```python
# Startup age and funding velocity
current_year = pd.Timestamp.now().year
# Convert 'founded_year' column to numeric, handling errors
df['founded_year'] = pd.to_numeric(df['founded_year'], errors='coerce')
df['Age_of_startup'] = current_year - df['founded_year']
df['Funding_velocity'] = df[' funding_total_usd '] / df['Age_of_startup']
```

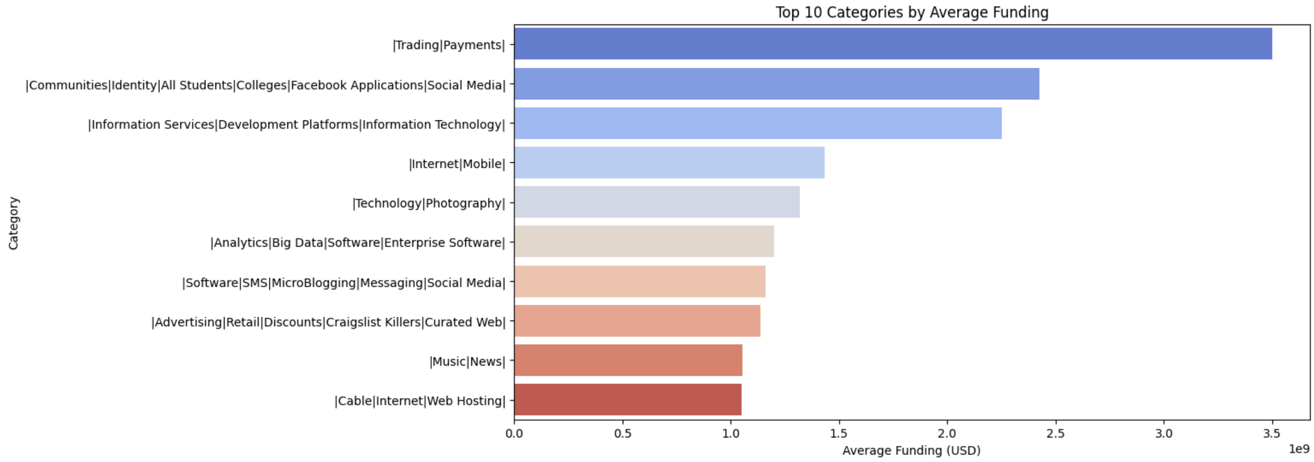
Advance EDA

```python
# Total funding by category, avg funding in each category
# Group by category and calculate total and average funding
category_funding = df.groupby('category_list')[' funding_total_usd '].agg(['sum', 'mean']).reset_index()
category_funding.rename(columns={'sum': 'total_funding', 'mean': 'average_funding'}, inplace=True)

# Create separate variables for total and average funding
top_by_total = category_funding.sort_values('total_funding', ascending=False).head(10)
top_by_average = category_funding.sort_values('average_funding', ascending=False).head(10)

# Plot Total Funding
plt.figure(figsize=(12, 6))
sns.barplot(data=top_by_total, x='total_funding', y='category_list', palette='viridis')
plt.title('Top 10 Categories by Total Funding')
plt.xlabel('Total Funding (USD)')
plt.ylabel('Category')
plt.show()

# Plot Average Funding
plt.figure(figsize=(12, 6))
sns.barplot(data=top_by_average, x='average_funding', y='category_list', palette='coolwarm')
plt.title('Top 10 Categories by Average Funding')
plt.xlabel('Average Funding (USD)')
plt.ylabel('Category')
plt.show()
```

```
<ipython-input-128-14b14de528f7>:12: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set

  sns.barplot(data=top_by_total, x='total_funding', y='category_list', palette='viridis')
```




```
<ipython-input-128-14b14de528f7>:20: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set

  sns.barplot(data=top_by_average, x='average_funding', y='category_list', palette='coolwarm')
```

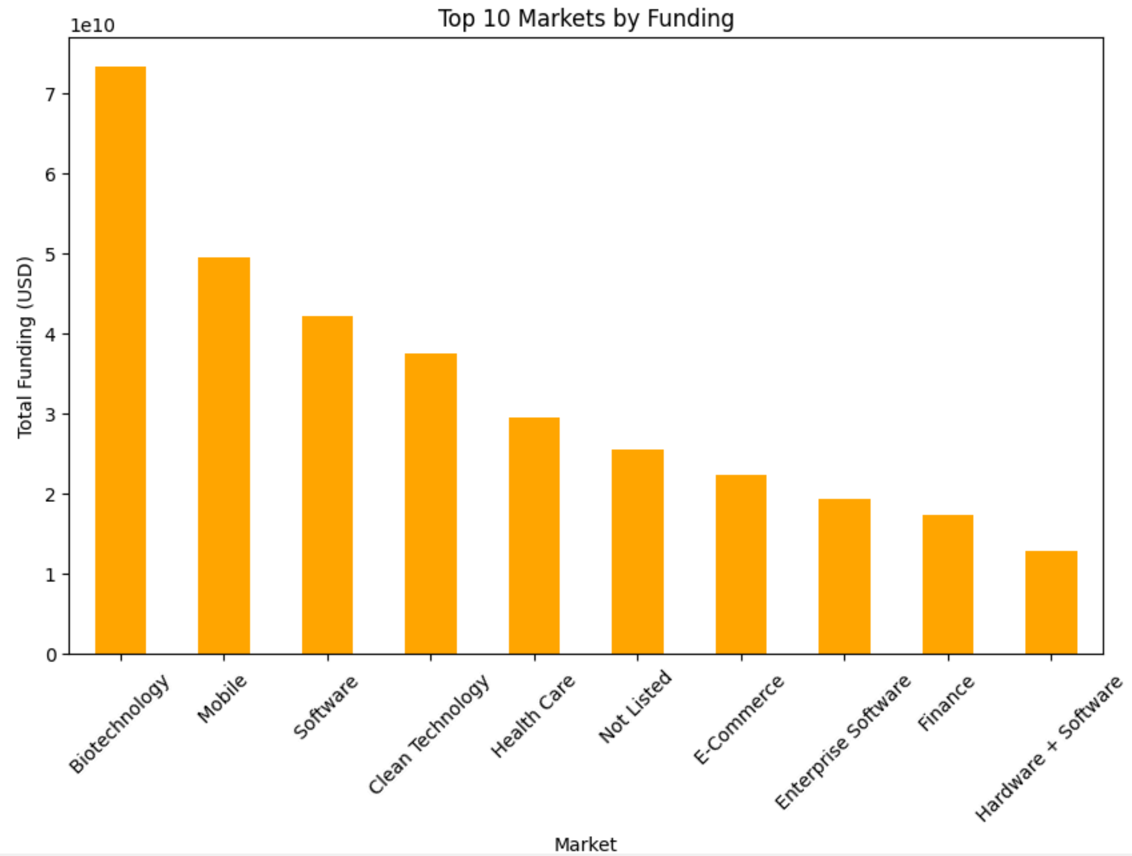


Insight:

1. Categories like Biotechnology, Mobile, Clean Technology, Software often top funding charts by Total funding, highlighting investor focus on technology-driven industries. The most funding is done for Biotechnology about 70 Billion Dollars.
2. Categories like Trading, Payments, Communities, college, students, social media often top funding charts by Average funding.The most avg funding is done for Trading & Payments about 3.5 Billion dollars.

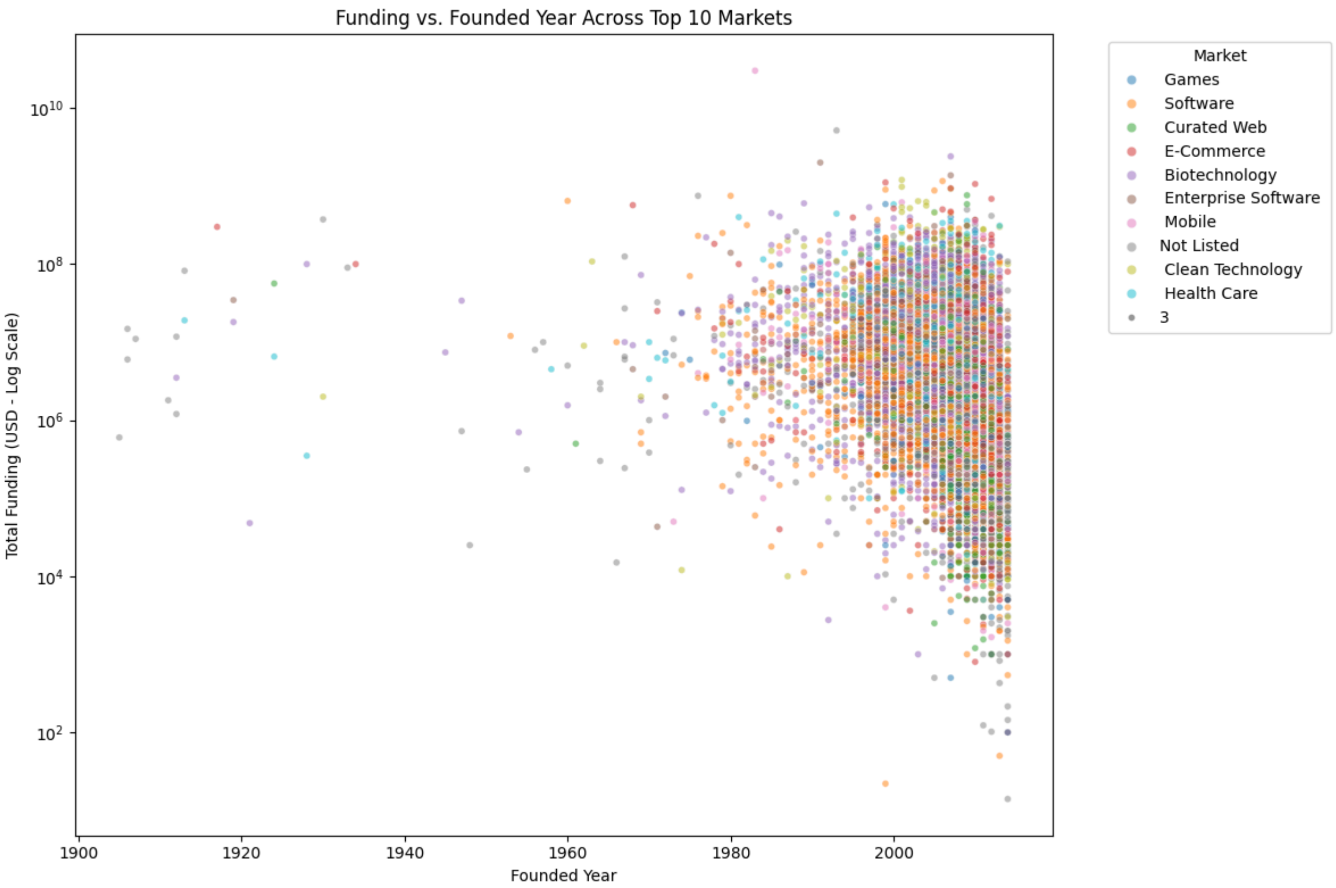
```
#Funding by Market
market_funding = df.groupby(' market ')[' funding_total_usd '].sum().sort_values(ascending=False).head(10)
market_funding.plot(kind='bar', figsize=(10, 6), color='orange')
plt.title('Top 10 Markets by Funding')
plt.xlabel('Market')
plt.ylabel('Total Funding (USD)')
```

```
plt.xticks(rotation=45)
plt.show()
```



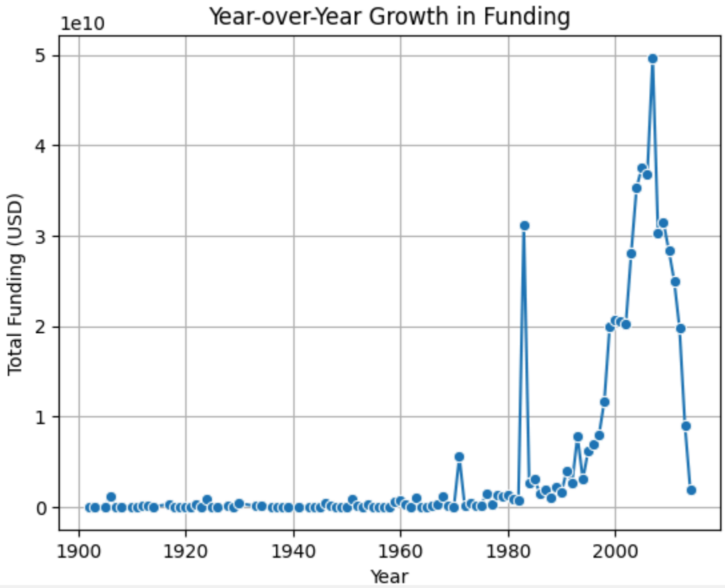
Insight: Markets such as Biotechnology, Mobile, Clean Technology, Software are among the most funded, reflecting their critical importance during recent economic trends. Biotechnology market has funded the most about 73 Billion dollars.

```
# Select the top 10 most frequent markets
top_markets = df[' market '].value_counts().head(10).index.tolist()

# Filter the data
filtered_df = df[df[' market '].isin(top_markets)]

# Create the scatter plot with the filtered data
plt.figure(figsize=(12, 8))
sns.scatterplot(data=filtered_df,
                x='founded_year',
                y=' funding_total_usd ',
                hue=' market ',
                alpha=0.5,
                size=3)

# Set the y-axis to logarithmic scale
plt.yscale('log')

# Add title and labels
plt.title('Funding vs. Founded Year Across Top 10 Markets')
plt.xlabel('Founded Year')
plt.ylabel('Total Funding (USD - Log Scale)')

# Adjust legend location if necessary
plt.legend(title='Market', bbox_to_anchor=(1.05, 1), loc='upper left')

plt.tight_layout()
plt.show()
```



Insight: The most striking insight is the dramatic surge in startup formation and funding post-1980s, with the peak funding reaching approximately 10 billion dollars (10^10) for top performers, particularly in Mobile and Biotechnology sectors, while the majority of startups receive funding between 1 million dollars(10^6) and 100 million dollars(10^8), demonstrating a significant expansion in the startup ecosystem during this four-decade period (1980-2020).

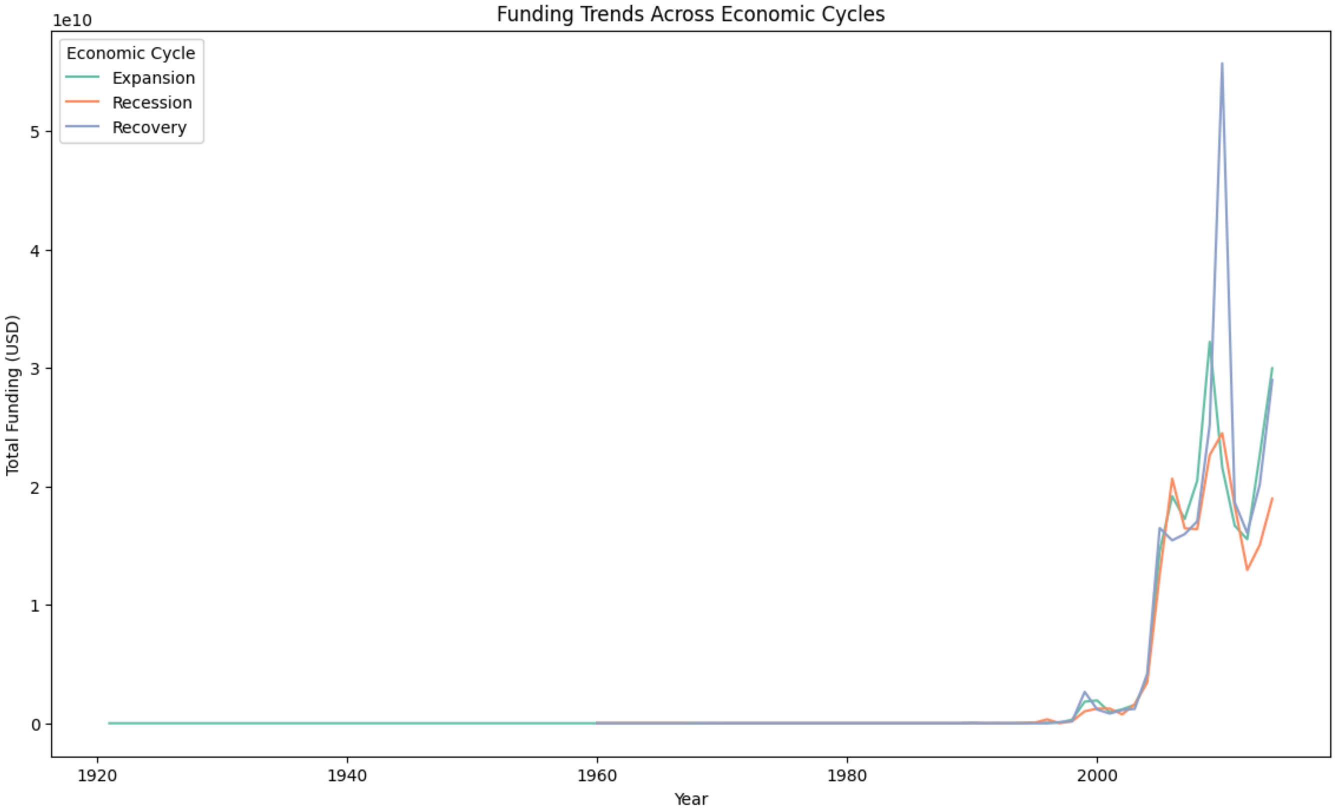
```
#Year-over-Year Growth in Funding
yearly_funding = df.groupby('founded_year')[' funding_total_usd '].sum().reset_index()
sns.lineplot(data=yearly_funding, x='founded_year', y=' funding_total_usd ', marker='o')
plt.title('Year-over-Year Growth in Funding')
plt.xlabel('Year')
plt.ylabel('Total Funding (USD)')
plt.grid(True)
plt.show()
```



Insight:

1. Startup funding experienced a dramatic surge around 2000-2005, reaching a peak of approximately $50 billion, followed by significant volatility, aligning with the dot-com bubble and subsequent recovery.
2. Prior to the late 1980s, startup funding was minimal, indicating a significant shift in the investment landscape over the past few decades.

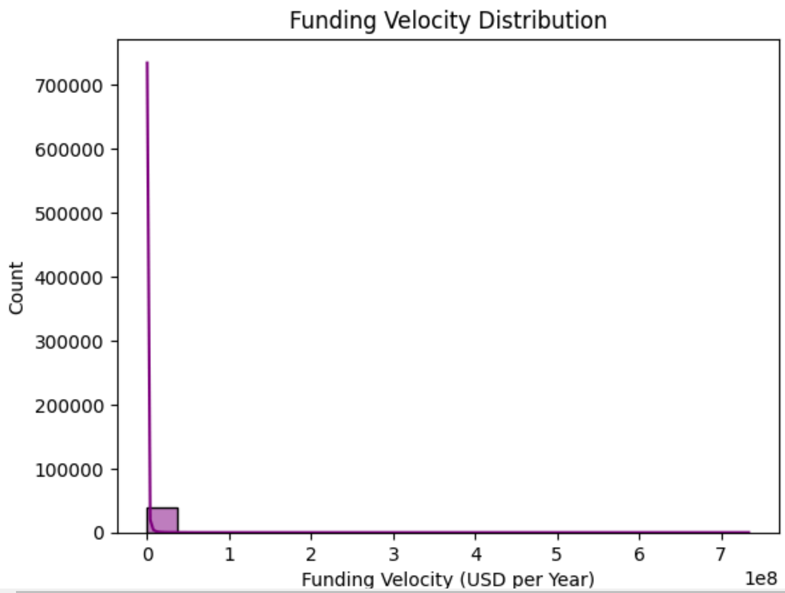
```
# Year-over-Year Funding Trends During Economic Cycles
# Add hypothetical economic cycle data
df['economic_cycle'] = ['Expansion', 'Recession', 'Recovery'] * (len(df) // 3) + ['Expansion'] * (len(df) % 3)

# Creating feature
df['funding_year'] = pd.to_datetime(df['first_funding_at'], errors='coerce').dt.year

# Group by funding year and economic cycle
economic_cycle_funding = df.groupby(['economic_cycle', 'funding_year'])[' funding_total_usd '].sum().reset_index()

# Visualization
plt.figure(figsize=(14, 8))
sns.lineplot(x='funding_year', y=' funding_total_usd ', hue='economic_cycle', data=economic_cycle_funding, palette='Set2')
plt.title('Funding Trends Across Economic Cycles')
plt.xlabel('Year')
plt.ylabel('Total Funding (USD)')
plt.legend(title='Economic Cycle')
plt.show()
```



Insight:

1. Startup funding exhibits a strong correlation with economic cycles, peaking during Recovery periods (approximately 55 billion) and reaching its lowest point during Recession periods (25 billion).
2. Before 1990, funding activity across all economic cycles was minimal, highlighting the significant growth and volatility of the startup funding landscape in recent decades.

```
# Funding Velocity
sns.histplot(df['Funding_velocity'], bins=20, kde=True, color='purple')
plt.title('Funding Velocity Distribution')
plt.xlabel('Funding Velocity (USD per Year)')
plt.ylabel('Count')
plt.show()
```



Insight:

1. The distribution of funding velocity is highly skewed, with the majority of startups (approximately 700,000) having near-zero funding velocity.
2. Only a small fraction of startups achieve rapid funding acceleration, with the maximum funding velocity reaching around 7x10^8 USD per year.

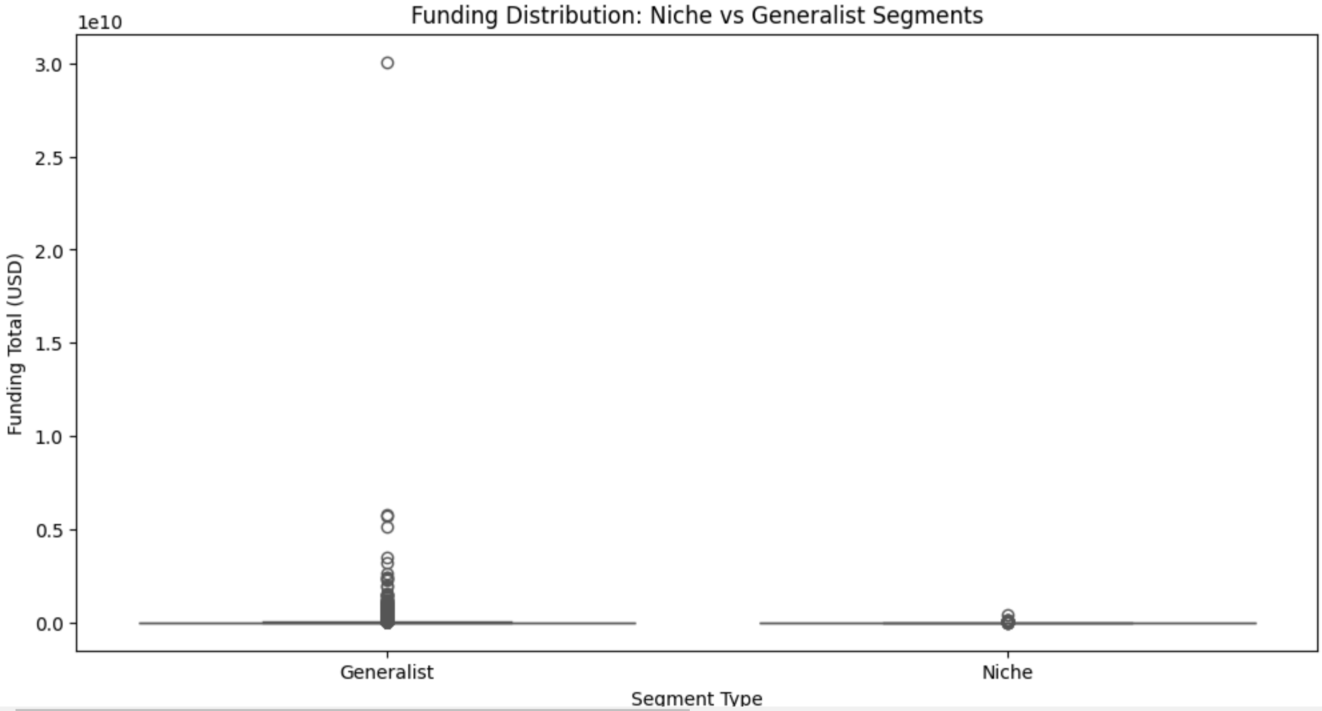
```
# Calculate the count of startups in each market
market_counts = df[' market '].value_counts()

# Define thresholds
niche_threshold = 2  # Example: Markets with ≤2 startups are considered "Niche"
generalist_threshold = 3  # Markets with >2 startups are "Generalist"

# Add a column for Niche/Generalist classification
df['segment_type'] = df[' market '].apply(
    lambda x: 'Niche' if market_counts[x] <= niche_threshold else 'Generalist'
)
```

```
# Niche vs. Generalist Segments
# Calculate average funding for Niche and Generalist segments
niche_funding = df[df['segment_type'] == 'Niche'][' funding_total_usd '].mean()
generalist_funding = df[df['segment_type'] == 'Generalist'][' funding_total_usd '].mean()

print(f"Average funding for Niche segments: ${niche_funding:,.2f}")
print(f"Average funding for Generalist segments: ${generalist_funding:,.2f}")
```

```
Average funding for Niche segments: $9,399,979.49
Average funding for Generalist segments: $13,183,965.45
```

```
plt.figure(figsize=(12, 6))
sns.boxplot(x='segment_type', y=' funding_total_usd ', data=df, palette='Set2')
plt.title('Funding Distribution: Niche vs Generalist Segments')
plt.xlabel('Segment Type')
plt.ylabel('Funding Total (USD)')
plt.show()
```

```
<ipython-input-136-38612e837d8c>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `x` variable to `hue` and set `le

  sns.boxplot(x='segment_type', y=' funding_total_usd ', data=df, palette='Set2')
```

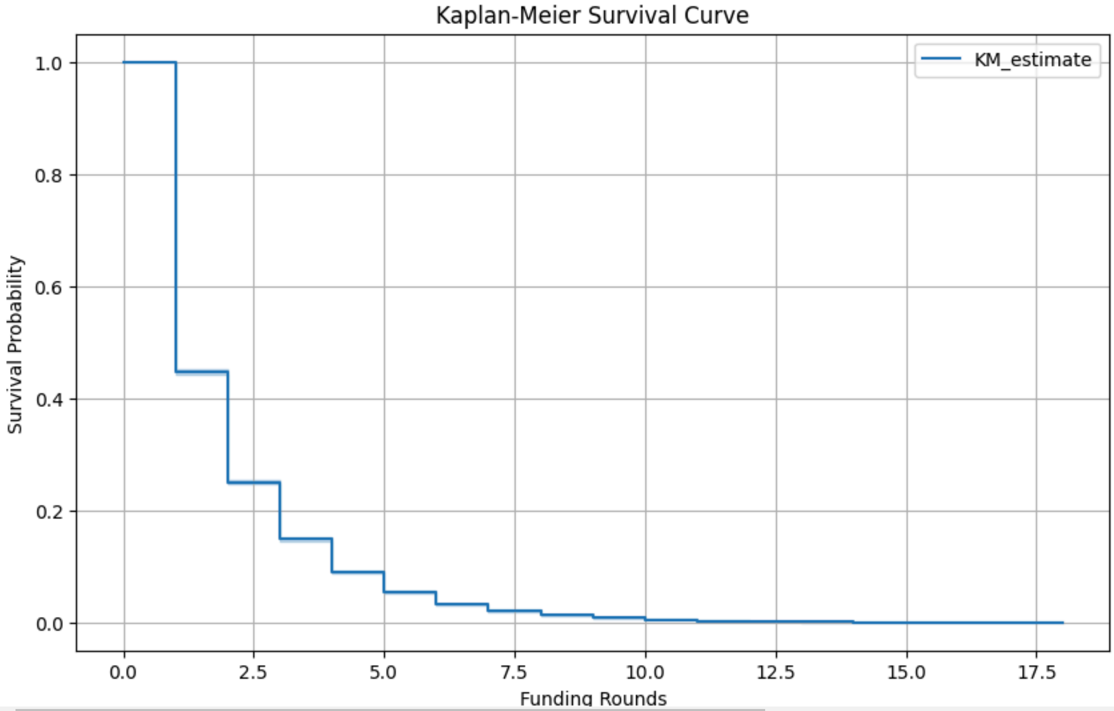


Insight:

1. While both niche and generalist segments have similar median funding levels, generalist segments exhibit a wider range of funding amounts, with some outliers reaching significantly higher values (up to 30 billion USD).
2. Niche segments tend to have a more concentrated funding distribution, with fewer high-value outliers and a maximum funding level around 1 billion USD.

```
#Survival Analysis Using Kaplan-Meier Estimator
!pip install lifelines
from lifelines import KaplanMeierFitter

kmf = KaplanMeierFitter()
kmf.fit(df['funding_rounds'], event_observed=(df['status'] == 'operating'))

plt.figure(figsize=(10, 6))
kmf.plot_survival_function()
plt.title('Kaplan-Meier Survival Curve')
plt.xlabel('Funding Rounds')
plt.ylabel('Survival Probability')
plt.grid(True)
plt.show()
```

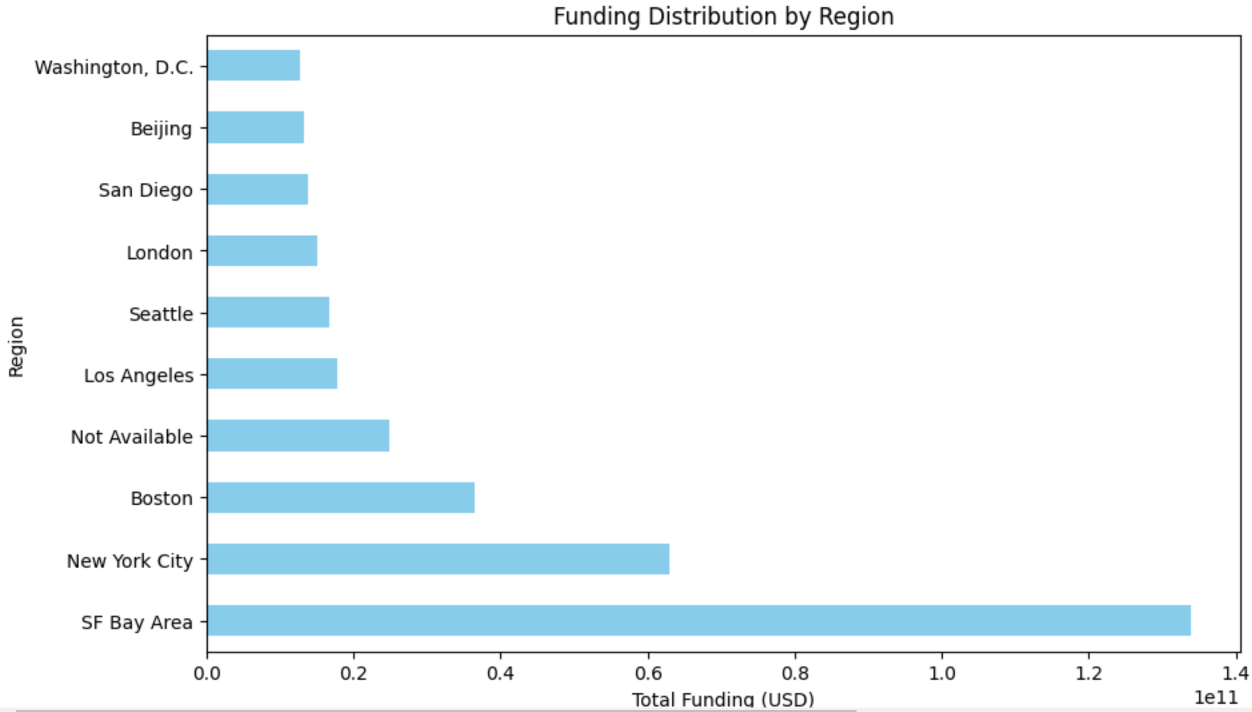
```
Requirement already satisfied: lifelines in /usr/local/lib/python3.10/dist-packages (0.30.0)
Requirement already satisfied: numpy>=1.14.0 in /usr/local/lib/python3.10/dist-packages (from lifelines) (1.26.4)
Requirement already satisfied: scipy>=1.7.0 in /usr/local/lib/python3.10/dist-packages (from lifelines) (1.13.1)
Requirement already satisfied: pandas>=2.1 in /usr/local/lib/python3.10/dist-packages (from lifelines) (2.2.2)
Requirement already satisfied: matplotlib>=3.0 in /usr/local/lib/python3.10/dist-packages (from lifelines) (3.8.0)
Requirement already satisfied: autograd>=1.5 in /usr/local/lib/python3.10/dist-packages (from lifelines) (1.7.0)
Requirement already satisfied: autograd-gamma>=0.3 in /usr/local/lib/python3.10/dist-packages (from lifelines) (0.5.0)
Requirement already satisfied: formulaic>=0.2.2 in /usr/local/lib/python3.10/dist-packages (from lifelines) (1.0.2)
Requirement already satisfied: interface-meta>=1.2.0 in /usr/local/lib/python3.10/dist-packages (from formulaic>=0.2.2->lifelines)
Requirement already satisfied: typing-extensions>=4.2.0 in /usr/local/lib/python3.10/dist-packages (from formulaic>=0.2.2->lifelines
Requirement already satisfied: wrapt>=1.0 in /usr/local/lib/python3.10/dist-packages (from formulaic>=0.2.2->lifelines) (1.16.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (1.3.1
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (4.54
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (1.4.7
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (24.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (11.0.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (3.2.0
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib>=3.0->lifelines) (2
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas>=2.1->lifelines) (2024.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.10/dist-packages (from pandas>=2.1->lifelines) (2024.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.10/dist-packages (from python-dateutil>=2.7->matplotlib>=3.0->life
```



Insight:

1. Startup survival probability decreases significantly after each funding round, with a sharp drop after the first round and continuing decline until around the fifth round.
2. The majority of startups fail to secure continued funding beyond the early stages, with only a small fraction surviving past 10 funding rounds.

```
#Bias Analysis
region_funding = df.groupby('region')[' funding_total_usd '].sum().sort_values(ascending=False).head(10)
region_funding.plot(kind='barh', figsize=(10, 6), color='skyblue')
plt.title('Funding Distribution by Region')
plt.xlabel('Total Funding (USD)')
plt.ylabel('Region')
plt.show()
```

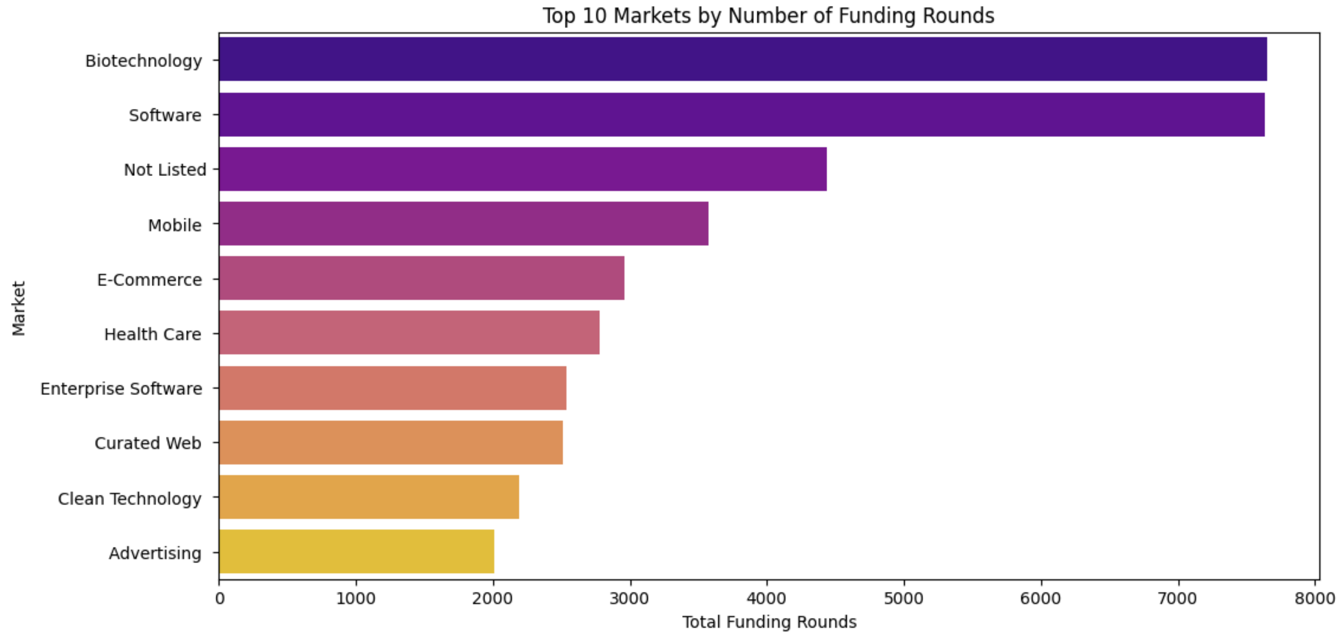


Insight:

1. The SF Bay Area dominates global startup funding, with approximately 140 billion USD, significantly outpacing other major tech hubs like New York City and Boston.
2. Geographical concentration is evident, with Silicon Valley and New York City attracting a disproportionate share of global startup funding.

```
#Number of funding rounds in each segment
# Group by market and count funding rounds
funding_rounds_by_segment = df.groupby(' market ')['funding_rounds'].sum().reset_index()

# Top 10 markets by funding rounds
top_funding_segments = funding_rounds_by_segment.sort_values('funding_rounds', ascending=False).head(10)

# Visualization
plt.figure(figsize=(12, 6))
sns.barplot(x='funding_rounds', y=' market ', data=top_funding_segments, palette='plasma')
plt.title('Top 10 Markets by Number of Funding Rounds')
plt.xlabel('Total Funding Rounds')
plt.ylabel('Market')
plt.show()
```

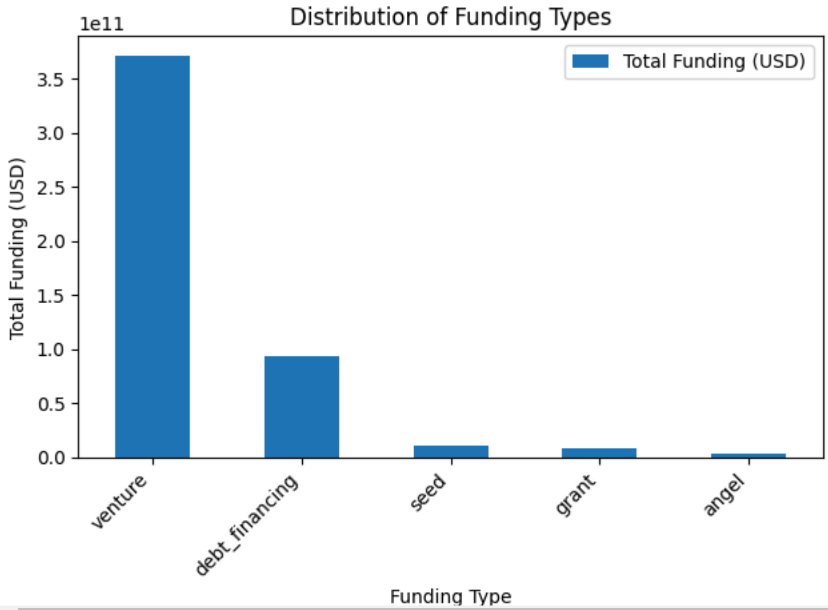
```
<ipython-input-139-2c4d09423010>:10: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in v0.14.0. Assign the `y` variable to `hue` and set `le

  sns.barplot(x='funding_rounds', y=' market ', data=top_funding_segments, palette='plasma')
```



Insight: Biotechnology market has received the highest number of funding rounds, with over 7,500 rounds, followed by Software with over 7,000 rounds, as Investors are more interested in these markets.

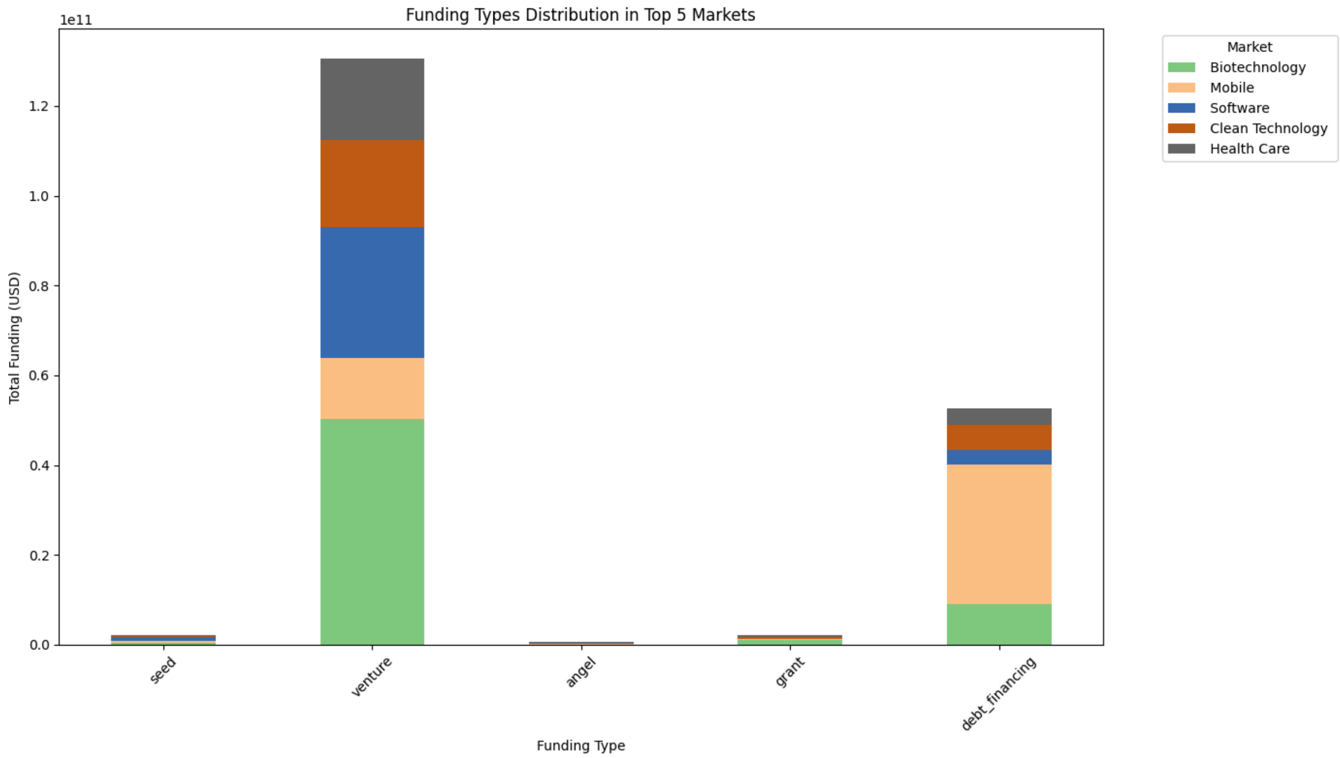
```
# Most common funding types in certain sectors
# Calculate total funding for each type
funding_types = ['seed', 'venture', 'angel', 'grant', 'debt_financing']
funding_type_totals = [df[funding_type].sum() for funding_type in funding_types]

# Create a DataFrame for the plot
funding_types_df = pd.DataFrame({
    'Funding Type': funding_types,
    'Total Funding (USD)': funding_type_totals
})

# Visualization
plt.figure(figsize=(12, 6))
funding_types_df.sort_values('Total Funding (USD)', ascending=False).plot(x='Funding Type', y='Total Funding (USD)', kind='bar')
plt.title('Distribution of Funding Types')
plt.xlabel('Funding Type')
plt.ylabel('Total Funding (USD)')
plt.xticks(rotation=45, ha='right')
plt.tight_layout()
plt.show()
```

<Figure size 1200x600 with 0 Axes>



Insight: Venture funding dominates with a total funding of approximately $3.7 billion, significantly surpassing other funding types like debt financing, seed funding, grants, and angel funding.

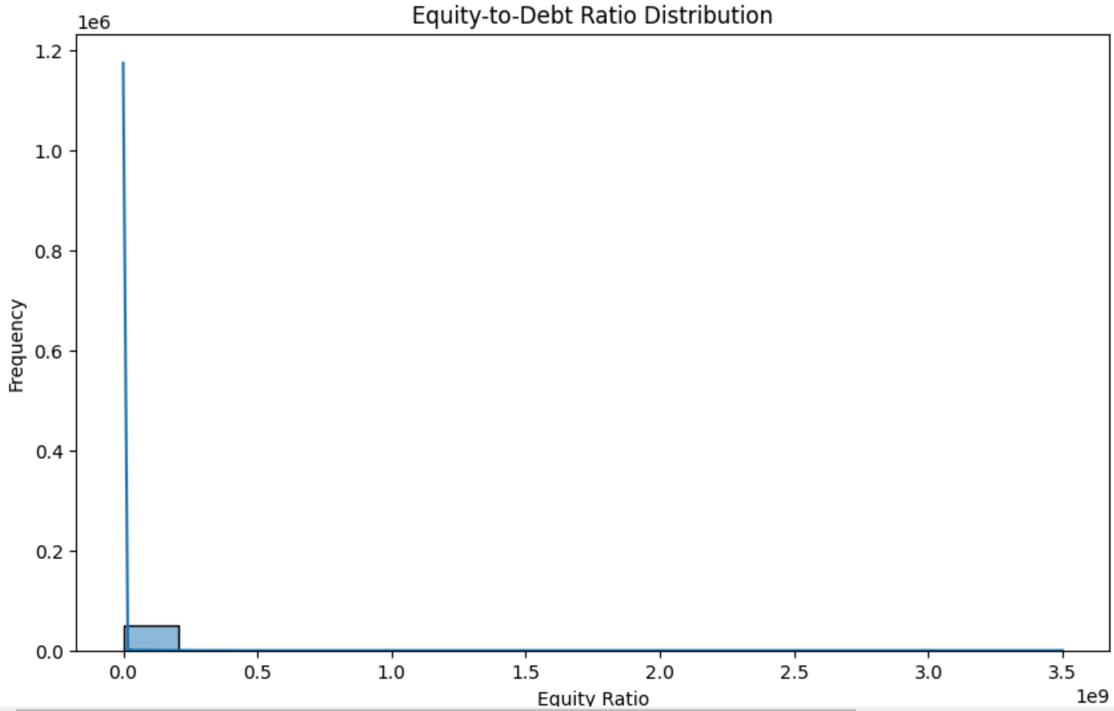
```
# Most Common Funding Types in Certain Sectors
# Aggregate funding types for each market
funding_types_by_market = df.groupby(' market ')[['seed', 'venture', 'angel', 'grant', 'debt_financing']].sum()

# Filter top 5 markets
top_markets = funding_types_by_market.sum(axis=1).sort_values(ascending=False).head(5)
top_markets_data = funding_types_by_market.loc[top_markets.index]

# Visualization
top_markets_data.T.plot(kind='bar', stacked=True, figsize=(14, 8), colormap='Accent')
plt.title('Funding Types Distribution in Top 5 Markets')
plt.xlabel('Funding Type')
plt.ylabel('Total Funding (USD)')
plt.xticks(rotation=45)
plt.legend(title='Market', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



Insight: Venture funding dominates in the top 5 markets, particularly in Biotechnology, with a total funding of approximately 1.1 billion, followed by Software with around $0.9 billion.

```
# Calculate equity-to-debt ratio
df['equity_ratio'] = df['private_equity'] / (df['debt_financing'] + 1)
print(df['equity_ratio'].describe())
# Visualization
plt.figure(figsize=(10, 6))
sns.histplot(df['equity_ratio'],kde = True)
plt.title('Equity-to-Debt Ratio Distribution')
plt.xlabel('Equity Ratio')
plt.ylabel('Frequency')
plt.show()
```

```
count    4.943800e+04
mean     1.793292e+06
std      2.952893e+07
min      0.000000e+00
25%      0.000000e+00
50%      0.000000e+00
75%      0.000000e+00
max      3.500000e+09
Name: equity_ratio, dtype: float64
```



The key insights from this data are:

The distribution is highly skewed, with a large peak at 0, meaning a significant number of startups have no equity financing at all and are completely debt-financed. There is a wide range of equity-to-debt ratios, from 0 to over 7 million, suggesting a diverse mix of financing strategies across the startups. The median and 75th percentile being at 0 indicate that more than half the startups have very low or no equity financing.

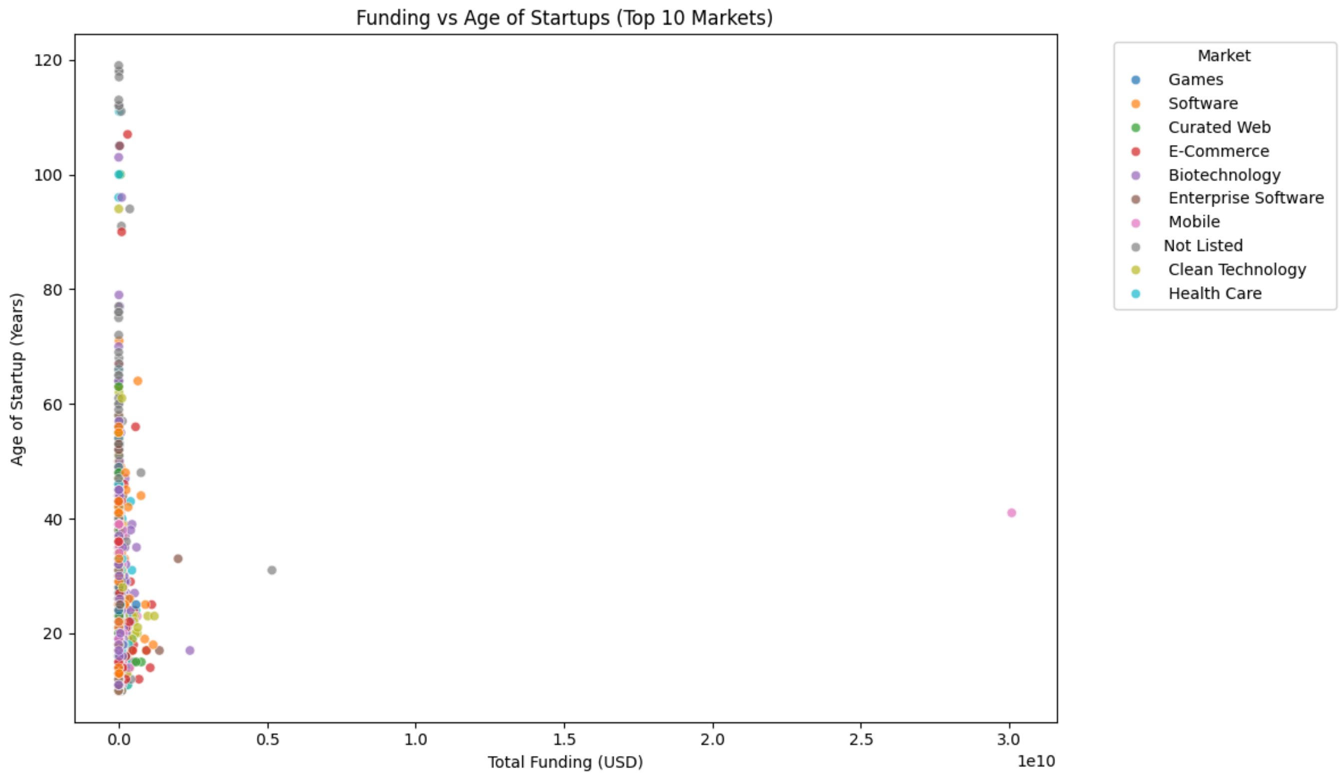
This implies that the startup funding landscape is dominated by debt-heavy financing structures, with a smaller number of startups relying more heavily on equity.

```
# Compare Round B and Round A funding
round_b_greater_a = (df['round_B'] > df['round_A']).mean()

print(f"Percentage of startups where Round B funding is greater than Round A: {round_b_greater_a * 100:.2f}%")
```

```
Percentage of startups where Round B funding is greater than Round A: 9.84%
```

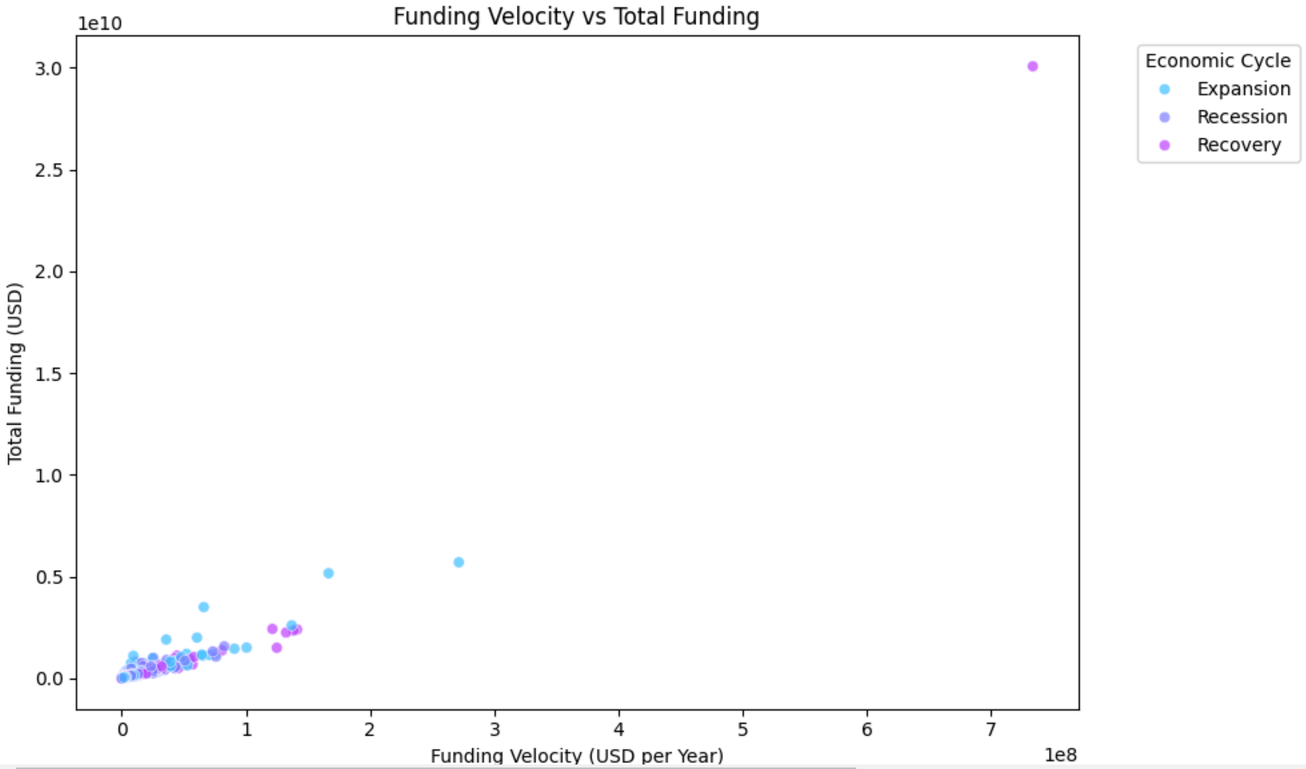
Insight: The analysis shows that, a relatively small portion of startups have a higher Round B funding compared to Round A, which indicate lower investor confidence, a cautious funding strategy or difficulties in getting to Series B.

```
# Get the top 10 markets by frequency
top_10_markets = df[' market '].value_counts().nlargest(10).index

# Filter the dataframe to include only the top 10 markets
df_top_markets = df[df[' market '].isin(top_10_markets)]

# Create the scatter plot
plt.figure(figsize=(12, 7))
sns.scatterplot(x=' funding_total_usd ', y='Age_of_startup', data=df_top_markets, alpha=0.7, hue=' market ', palette='tab10')
plt.title('Funding vs Age of Startups (Top 10 Markets)')
plt.xlabel('Total Funding (USD)')
plt.ylabel('Age of Startup (Years)')
plt.legend(title='Market', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



Insight: The scatter plot reveals a correlation between funding and age. Startups with higher funding, often exceeding 10 million, tend to be older, with some surpassing 100 years. However, there's a cluster of younger startups, less than 10 years old, securing funding below $10 million. This suggests that while funding can contribute to longevity, it's not the sole determinant.

```
#Trend Between Funding Velocity and Total Funding
# Scatter plot for funding velocity vs total funding
plt.figure(figsize=(10, 6))
sns.scatterplot(x='Funding_velocity', y=' funding_total_usd ', data=df, alpha=0.7, hue='economic_cycle', palette='cool')
plt.title('Funding Velocity vs Total Funding')
plt.xlabel('Funding Velocity (USD per Year)')
plt.ylabel('Total Funding (USD)')
plt.legend(title='Economic Cycle', bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```



Insight: The scatter plot reveals a positive correlation between funding velocity and total funding. Startups with higher funding velocities, exceeding 100 million USD per year, tend to secure more total funding, often surpassing 10 billion USD. However, startups with lower funding velocities, below 100 million USD per year, and total funding below 10 billion USD also exist. This suggests that while a higher funding velocity can contribute to increased total funding, other factors like market demand and team experience also influence a startup's success. Additionally, economic cycles impact funding velocity and total funding, with expansion periods generally leading to higher values.

Statistical Testing

```
from scipy.stats import ttest_ind

us_funding = df[df['country_code'] == 'USA'][' funding_total_usd ']
non_us_funding = df[df['country_code'] != 'USA'][' funding_total_usd ']

t_stat, p_value = ttest_ind(us_funding, non_us_funding, nan_policy='omit')
print(f"T-Statistic: {t_stat}, P-Value: {p_value}")

# Observation
if p_value < 0.05:
    print("Significant difference in funding between US and non-US startups.")
else:
    print("No significant difference in funding between US and non-US startups.")
```

```
T-Statistic: 5.057601708836089, P-Value: 4.260772022422439e-07
Significant difference in funding between US and non-US startups.
```

Insight: A low p-value (< 0.05) indicates significant differences in funding between US and non-US startups.

```
#Test Whether Specific Markets Receive Significantly Higher Funding Than Others
from scipy.stats import ttest_ind

# Extract funding data for specific markets
software_funding = df[df[' market '] == 'Software'][' funding_total_usd ']
ecommerce_funding = df[df[' market '] == 'E-Commerce'][' funding_total_usd ']

# Perform t-test
t_stat, p_value = ttest_ind(software_funding, ecommerce_funding, nan_policy='omit')

# Observation
if p_value < 0.05:
    print("Significant difference in funding between Software and E-Commerce markets.")
else:
    print("No significant difference in funding between Software and E-Commerce markets.")
```

```
No significant difference in funding between Software and E-Commerce markets.
```

```
#Test Whether Startups in Urban Regions Receive More Funding Than Those in Rural Regions
# Define urban and rural cities
urban_cities = ['SF Bay Area', 'New York City', 'London', 'Boston']
df['region_type'] = df['city'].apply(lambda x: 'Urban' if x in urban_cities else 'Rural')

# Perform t-test
urban_funding = df[df['region_type'] == 'Urban'][' funding_total_usd ']
rural_funding = df[df['region_type'] == 'Rural'][' funding_total_usd ']

t_stat, p_value = ttest_ind(urban_funding, rural_funding, nan_policy='omit')
print(f"T-Statistic: {t_stat}, P-Value: {p_value}")

# Observation
if p_value < 0.05:
    print("Significant difference in funding between Urban and Rural regions.")
else:
    print("No significant difference in funding between Urban and Rural regions.")
```

```
T-Statistic: -0.7030947579620268, P-Value: 0.4820000097168825
No significant difference in funding between Urban and Rural regions.
```

```
#Test the Impact of Funding Type on Total Funding
venture_funding = df[df['venture'] > 0][' funding_total_usd ']
debt_funding = df[df['debt_financing'] > 0][' funding_total_usd ']

# Perform t-test
t_stat, p_value = ttest_ind(venture_funding, debt_funding, nan_policy='omit')
print(f"T-Statistic: {t_stat}, P-Value: {p_value}")

# Observation
if p_value < 0.05:
    print("Significant difference in total funding between venture and debt financing.")
else:
    print("No significant difference in total funding between venture and debt financing.")
```

```
T-Statistic: -6.741703977651515, P-Value: 1.5963452598700614e-11
Significant difference in total funding between venture and debt financing.
```

```
#Test if Startups Founded in Different Economic Cycles Receive Different Levels of Funding
# Define economic cycles (example years for illustration)
from scipy.stats import f_oneway

# Extract funding data for each economic cycle
expansion_funding = df[df['economic_cycle'] == 'Expansion'][' funding_total_usd '].dropna()
recession_funding = df[df['economic_cycle'] == 'Recession'][' funding_total_usd '].dropna()
recovery_funding = df[df['economic_cycle'] == 'Recovery'][' funding_total_usd '].dropna()

# Perform one-way ANOVA
f_stat, p_value = f_oneway(expansion_funding, recession_funding, recovery_funding)

# Print the results
print(f"F-Statistic: {f_stat:.4f}, P-Value: {p_value:.4f}")

# Observation
if p_value < 0.05:
    print("Significant differences in funding between economic cycles.")
else:
    print("No significant differences in funding between economic cycles.")
```

```
F-Statistic: 1.8294, P-Value: 0.1605
No significant differences in funding between economic cycles.
```

```
#We test whether the average funding for Niche segments differs significantly from Generalist segments.
from scipy.stats import ttest_ind

# Funding for Niche and Generalist segments
niche_funding_data = df[df['segment_type'] == 'Niche'][' funding_total_usd '].dropna()
generalist_funding_data = df[df['segment_type'] == 'Generalist'][' funding_total_usd '].dropna()

# Perform t-test
t_stat, p_value = ttest_ind(niche_funding_data, generalist_funding_data, nan_policy='omit')
print(f"T-Statistic: {t_stat:.4f}, P-Value: {p_value:.4f}")

# Observation
if p_value < 0.05:
```

```
    print("Significant difference in funding between Niche and Generalist segments.")
else:
    print("No significant difference in funding between Niche and Generalist segments.")
```

```
T-Statistic: -0.3696, P-Value: 0.7117
No significant difference in funding between Niche and Generalist segments.
```

Insights

Observations :

1. There are total 49436 unique permalink.
2. There are 49350 unique names of the startup in the dataset.
3. There are 753 unique market listed in the dataset.
4. There are 1089 unique regions mentioned in the dataset.
5. The dataset needs data cleaning as we can see the there are hyphens(garbage value) present in the columns.

Insights:

1. Categories like Biotechnology, Mobile, Clean Technology, Software often top funding charts by Total funding, highlighting investor focus on technology-driven industries. The most funding is done for Biotechnology about 70 Billion Dollars.
2. Categories like Trading, Payments, Communities, college, students, social media often top funding charts by Average funding. The most avg funding is done for Trading & Payments about 3.5 Billion dollars.
3. Markets such as Biotechnology, Mobile, Clean Technology, Software are among the most funded, reflecting their critical importance during recent economic trends. Biotechnology market has funded the most about 73 Billion dollars.
4. The most striking insight is the dramatic surge in startup formation and funding post-1980s, with the peak funding reaching approximately 10 billion dollars (10^10) for top performers, particularly in Mobile and Biotechnology sectors, while the majority of startups receive funding between 1 million dollars(10^6) and 100 million dollars(10^8), demonstrating a significant expansion in the startup ecosystem during this four-decade period (1980-2020).
5. Startup funding experienced a dramatic surge around 2000-2005, reaching a peak of approximately 50 billion, followed by significant volatility, aligning with the dot-com bubble and subsequent recovery.
6. Prior to the late 1980s, startup funding was minimal, indicating a significant shift in the investment landscape over the past few decades.
7. Startup funding exhibits a strong correlation with economic cycles, peaking during Recovery periods (approximately 55 billion) and reaching its lowest point during Recession periods (25 billion).
8. Before 1990, funding activity across all economic cycles was minimal, highlighting the significant growth and volatility of the startup funding landscape in recent decades.
9. The distribution of funding velocity is highly skewed, with the majority of startups (approximately 700,000) having near-zero funding velocity.
10. Only a small fraction of startups achieve rapid funding acceleration, with the maximum funding velocity reaching around 7x10^8 USD per year.
11. Average funding for Niche segments: 9,399,979.49
12. Average funding for Generalist segments: 13,183,965.45
13. While both niche and generalist segments have similar median funding levels, generalist segments exhibit a wider range of funding amounts, with some outliers reaching significantly higher values (up to 30 billion USD).
14. Niche segments tend to have a more concentrated funding distribution, with fewer high-value outliers and a maximum funding level around 1 billion USD.
15. Startup survival probability decreases significantly after each funding round, with a sharp drop after the first round and continuing decline until around the fifth round.
16. The majority of startups fail to secure continued funding beyond the early stages, with only a small fraction surviving past 10 funding rounds.
17. The SF Bay Area dominates global startup funding, with approximately 140 billion USD, significantly outpacing other major tech hubs like New York City and Boston.
18. Geographical concentration is evident, with Silicon Valley and New York City attracting a disproportionate share of global startup funding.
19. Biotechnology market has received the highest number of funding rounds, with over 7,500 rounds, followed by Software with over 7,000 rounds, as Investors are more interested in these markets.
20. Venture funding dominates with a total funding of approximately 3.7 billion, significantly surpassing other funding types like debt financing, seed funding, grants, and angel funding.
21. Venture funding dominates in the top 5 markets, particularly in Biotechnology, with a total funding of approximately 1.1 billion, followed by Software with around 0.9 billion.
22. The distribution is highly skewed, with a large peak at 0, meaning a significant number of startups have no equity financing at all and are completely debt-financed. There is a wide range of equity-to-debt ratios, from 0 to over 7 million, suggesting a diverse mix of financing strategies across the startups. The median and 75th percentile being at 0 indicate that more than half the startups have very low or no

equity financing. This implies that the startup funding landscape is dominated by debt-heavy financing structures, with a smaller number of startups relying more heavily on equity.

23. The analysis shows that, a relatively small portion of startups have a higher Round B funding compared to Round A, which indicate lower investor confidence, a cautious funding strategy or difficulties in getting to Series B.
24. The scatter plot reveals a correlation between funding and age. Startups with higher funding, often exceeding 10 million, tend to be older, with some surpassing 100 years. However, there's a cluster of younger startups, less than 10 years old, securing funding below $10 million. This suggests that while funding can contribute to longevity, it's not the sole determinant.
25. The scatter plot reveals a positive correlation between funding velocity and total funding. Startups with higher funding velocities, exceeding 100 million USD per year, tend to secure more total funding, often surpassing 10 billion USD. However, startups with lower funding velocities, below 100 million USD per year, and total funding below 10 billion USD also exist. This suggests that while a higher funding velocity can contribute to increased total funding, other factors like market demand and team experience also influence a startup's success. Additionally, economic cycles impact funding velocity and total funding, with expansion periods generally leading to higher values.

Statistical Testing :

1. A low p-value (< 0.05) indicates significant differences in funding between US and non-US startups.
2. No significant difference in funding between Software and E-Commerce markets.
3. No significant difference in funding between Urban and Rural regions.
4. Significant difference in total funding between venture and debt financing.
5. No significant differences in funding between economic cycles.
6. No significant difference in funding between Niche and Generalist segments.

Recommendations:

1. Portfolio Diversification:

Recommendation: Diversify investment portfolios across multiple high-potential sectors, such as Biotechnology, Mobile, and Software. These sectors have consistently received the highest funding levels, indicating strong investor interest and growth potential.

Rationale: Diversifying across sectors helps mitigate risk and capture opportunities in fast-moving, technology-driven industries.

2. Geographic Expansion:

Recommendation: Explore investment opportunities outside the traditional startup hubs of the SF Bay Area and New York City. Consider incentivizing entrepreneurship in other regions to identify and support promising startups in emerging markets.

Rationale: The data shows a significant funding concentration in Silicon Valley and NYC. Expanding into other regions can provide access to untapped talent and innovative ideas, potentially yielding higher returns.

3. Targeted Funding Strategies:

Recommendation: Develop tailored programs and resources to help startups navigate the critical early funding rounds. Focus on supporting startups through the sharp drop-off in survival rates after the first few rounds.

Rationale: The Kaplan-Meier Survival Curve highlights the challenges startups face in securing continued funding, especially after the initial rounds. Targeted interventions can improve sustainability and increase the likelihood of successful exits.

4. Niche Segment Support:

Recommendation: Allocate a portion of investment capital to support niche/specialized startups, as they appear to receive lower funding compared to generalist segments, despite potentially filling important market gaps.

Rationale: Niche startups may offer unique value propositions and opportunities for differentiation. Providing tailored support and funding can help these companies thrive and diversify the investment portfolio.

5. Economic Cycle Responsiveness:

Recommendation: Closely monitor economic cycles and be prepared to adjust investment strategies accordingly. Allocate more resources during recovery periods when funding tends to surge, and maintain a more conservative approach during recessions.

Rationale: The data shows a strong correlation between funding levels and economic cycles, with recovery periods experiencing the highest funding peaks. Adaptability to these trends can improve investment timing and returns.

6. Financing Structure Analysis:

Recommendation: Investigate ways to encourage a more balanced debt-to-equity financing structure among startups, as the current landscape appears heavily skewed towards debt-heavy models.