Data Bootcamp Final Project

ECON-UB 232

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Introduction ¶

Over the past half a decade, there has been a huge effort by companies of all industries to expand their grounds of diversity in an attempt to promote an open-minded and welcoming atmosphere for their employees. The idea is that diversity fosters creativity of different thoughts and ideas which can give rise to more efficient solutions outside the scope of traditional thinking. Initially, the diversity within business movement began in the 1960s as a part of a societal push for businesses to comply with the objectives of equal opportunity employment act [1]. Through the expansion of diversity, however, companies speculated the existence of benefits of greater innovation that could be derived from teams of a wider variety of backgrounds. This social justice model, originally created to stimulate equal employment opportunity for people of all different identities, quickly evolved into an assumed way for corporations to become more profitable, leading to the large-scale diversity recruiting programs we see today.

In various business models, it is projected that corporations lacking strong inclusion of diversity inherently are less productive, have a negative work culture, as well as a higher employee turnover rate. A Mckinsey report also claims that these not only directly affect the company through decreased efficiency and performance but also through the heightened costs. Due to the turnover rates, whether that be a loss of time, loss of resources, and loss of money spent on the ex-employees companies incur large costs associated with this problem [2]. In addition, organizations that plan to expand into global markets, believe that a diverse team will cause them to appear more externally inviting. Additionally internally, corporations claim further benefits of greater creativity, higher productivity, quicker problem solving and enhanced decision making.

In our freshman CLP class, many of these same claims were made about diversity’s huge benefits. However, they didn’t provide us with any statistical data on the matter which made us call into question the validity of the claims. We wanted to know if the huge advantages given to diversity candidates were actually helping a company’s profitability in the ways they said it is or if there was an alternative motive, such as better optics for the company. So, we decided to look at the industry where diversity is most highly regarded, tech [5].

This project focuses on diversity in the tech sector and its impact on companies profitability. We examined the data on the correlation of diversity on EBITDA to test these assertions made in our CLP class and in the business world.

Note: There are more factors besides the ability to yield a profit that determines a company’s success. However, financial data is the most abundant and quantitatively driven source of information that is available to us.

Exploring and importing overall diversity data

First, we will import numpy, pandas, and pyplot to assist future data cleaning, management, and presentation.

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

Let's import our first dataset. The dataset `tech_diversity` contains 2016 sector-wide demographic information that informs us of the overall diversity landscape among tech companies. We used EEO-1 forms filled out by Silicon Valley companies from the Equal Employment Opportunity Commision to retrieve information about the racial breakdown down of these companies by job title. [6]

In [2]:
```
tech_diversity = pd.read_csv("C:/Users/weiti/Desktop/Freshman Fall/ECON-UB 23
2/finalProject/Tech_sector_diversity_demographics_2016.csv")
tech_diversity = tech_diversity.loc[(tech_diversity['race_ethnicity'] != 'All'
) &
                                    (tech_diversity['race_ethnicity'] != 'Tota
ls') &
                                    (tech_diversity['gender'] != 'Both'),]
tech_diversity
```

Out[2]:

	job_category	race_ethnicity	gender	count	percentage
0	All workers	White	Male	268883	41.257252
1	All workers	White	Female	105560	16.197065
2	All workers	Black_or_African American	Male	17508	2.686417
3	All workers	Black_or_African American	Female	11479	1.761331
4	All workers	Asian	Male	125347	19.233171
5	All workers	Asian	Female	58049	8.907005
6	All workers	Hispanic_or_Latino	Male	32201	4.940903
7	All workers	Hispanic_or_Latino	Female	15512	2.380152
11	Executives	White	Male	7282	58.678485
12	Executives	White	Female	1818	14.649476
13	Executives	Black_or_African American	Male	120	0.966962
14	Executives	Black_or_African American	Female	53	0.427075
15	Executives	Asian	Male	2023	16.301370
16	Executives	Asian	Female	556	4.500000
17	Executives	Hispanic_or_Latino	Male	266	2.143433
18	Executives	Hispanic_or_Latino	Female	103	0.829976
22	Managers	White	Male	48311	46.479253
23	Managers	White	Female	18935	18.217065
24	Managers	Black_or_African American	Male	1575	1.515283
25	Managers	Black_or_African American	Female	978	0.940918
26	Managers	Asian	Male	18563	17.859170
27	Managers	Asian	Female	8084	7.777489
28	Managers	Hispanic_or_Latino	Male	3741	3.599157
29	Managers	Hispanic_or_Latino	Female	1642	1.579742
33	Professionals	White	Male	133311	38.660592
34	Professionals	White	Female	47505	13.776593
35	Professionals	Black_or_African American	Male	6301	1.827309
36	Professionals	Black_or_African American	Female	3756	1.089251
37	Professionals	Asian	Male	89365	25.916120
38	Professionals	Asian	Female	39902	11.571700
39	Professionals	Hispanic_or_Latino	Male	11820	3.427836
40	Professionals	Hispanic_or_Latino	Female	5533	1.604587

Variable Breakdown for Tech Diversity Data Frame

company: Name of the company

year: 2016

race: Possible values: "American_Indian_Alaskan_Native", "Asian", "Black_or_African_American", "Latino", "Native_Hawaiian_or_Pacific_Islander", "Two_or_more_races", "White", "Overall_totals"

gender: Possible values: "male", "female". Non-binary gender is not counted in EEO-1 reports.

job_category: Possible values: "Administrative support", "Craft workers", "Executive/Senior officials & Mgrs", "First/Mid officials & Mgrs", "laborers and helpers", "operatives", "Professionals", "Sales workers", "Service workers", "Technicians", "Previous_totals", "Totals"

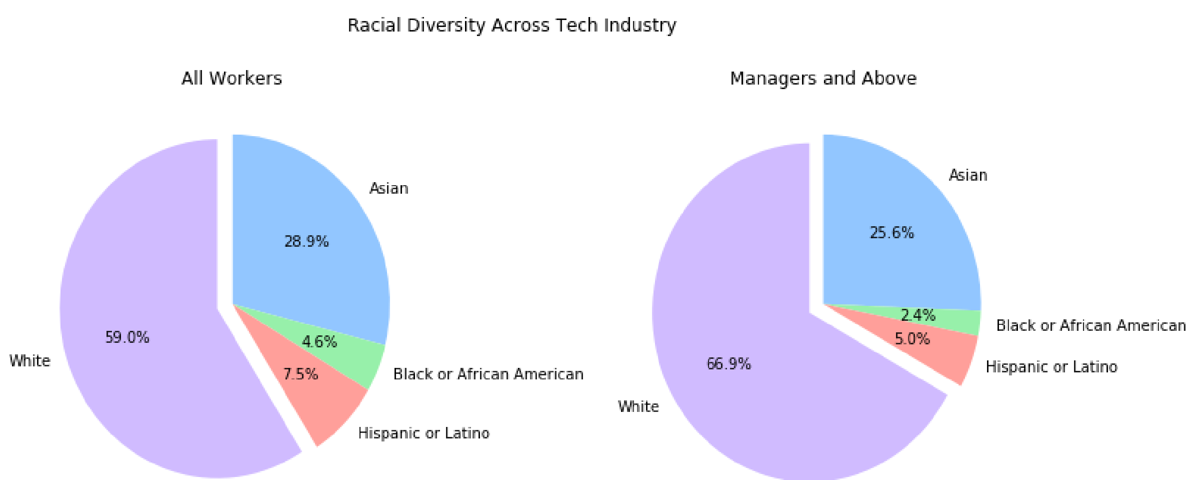
count: Mostly integer values, but contains "na" for a no-data variable.

Let's take a look at the racial and gender distribution within tech industry as a whole. However, for labeling purposes, let's write a function that replaces all underscores with spaces first.

In [3]:
```
def underscore_to_space(input):
    output = [s.replace('_',' ') for s in input]
    return output
```

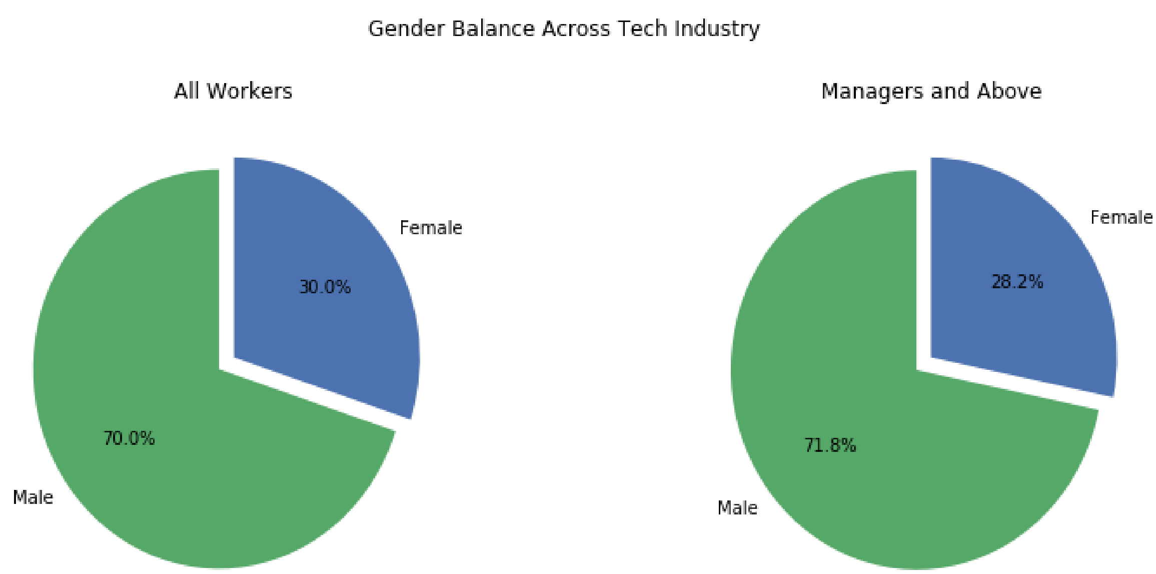
Now we will examine the racial diversity across all workers and the racial diversity exhibited by managerial level and above. We aggregate gender counts to get overall race counts, then we produce the pie charts below:

In [4]:
```
workerCondition = tech_diversity['job_category'] == 'All workers'

race_overall = tech_diversity.loc[workerCondition,].groupby('race_ethnicity',
as_index = False).agg({'count':np.sum})
race_overall['percentage'] = 100 * race_overall['count'] / np.sum(race_overall
['count'])

workerCondition = (tech_diversity['job_category'] == 'Executives') | (tech_div
ersity['job_category'] == 'Managers')

race_execmgmt = tech_diversity.loc[workerCondition,].groupby('race_ethnicity',
 as_index = False).agg({'count':np.sum})
race_execmgmt['percentage'] = 100 * race_execmgmt['count'] / np.sum(race_execm
gmt['count'])

plt.style.use('seaborn-pastel')

fig, axarr = plt.subplots(1, 2, figsize = (12,5.5))
axarr[0].pie(x = race_overall['percentage'], labels = underscore_to_space(race
_overall['race_ethnicity']),
             startangle = 90, autopct = '%1.1f%%', counterclock = False, explo
de = (0,0,0,0.1))
axarr[0].set(title = 'All Workers')
axarr[1].pie(x = race_execmgmt['percentage'], labels = underscore_to_space(rac
e_execmgmt['race_ethnicity']),
             startangle = 90, autopct = '%1.1f%%', counterclock = False, explo
de = (0,0,0,0.1))
axarr[1].set(title = 'Managers and Above')
fig.suptitle('Racial Diversity Across Tech Industry')
fig.subplots_adjust(wspace = 0.5, top = 0.85)
```



It seems like, overall, Tech industry is dominated by white and asian races and is especially so on managerial and executive levels. Let's repeat the same exercise on gender by examining male-female compositions:

In [5]:
```
workerCondition = tech_diversity['job_category'] == 'All workers'

gender_overall = tech_diversity.loc[workerCondition,].groupby('gender', as_ind
ex = False).agg({'count':np.sum})
gender_overall['percentage'] = 100 * gender_overall['count'] / np.sum(gender_o
verall['count'])

workerCondition = (tech_diversity['job_category'] == 'Executives') | (tech_div
ersity['job_category'] == 'Managers')

gender_execmgmt = tech_diversity.loc[workerCondition,].groupby('gender', as_in
dex = False).agg({'count':np.sum})
gender_execmgmt['percentage'] = 100 * gender_execmgmt['count'] / np.sum(gender
_execmgmt['count'])

plt.style.use('seaborn-deep')

fig, axarr = plt.subplots(1, 2, figsize = (12,5.5))
axarr[0].pie(x = gender_overall['percentage'], labels = underscore_to_space(ge
nder_overall['gender']),
             startangle = 90, autopct = '%1.1f%%', counterclock = False, explo
de = (0,0.1))
axarr[0].set(title = 'All Workers')
axarr[1].pie(x = gender_execmgmt['percentage'], labels = underscore_to_space(g
ender_execmgmt['gender']),
             startangle = 90, autopct = '%1.1f%%', counterclock = False, explo
de = (0,0.1))
axarr[1].set(title = 'Managers and Above')
fig.suptitle('Gender Balance Across Tech Industry')
fig.subplots_adjust(wspace = 0.5, top = 0.85)
```



The gender balance is even worse than racial diversity in tech industries, and, in both cases, the imbalance is more significant at managerial levels and above.

Exploring and importing Silicon Valley tech company data

After exploring overall racial diversity and gender balance data across the industry, let's examine the tech companies in silicon valley. First, we will import the 2016 company-specific data and name the dataset `distribution_data_raw`.

In [6]:
```
distribution_data_raw = pd.read_csv("C:/Users/weiti/Desktop/Freshman Fall/ECON
-UB 232/finalProject/Distributions_data_2016.csv")
distribution_data_raw.head(5)
```

Out[6]:

	company	percentage	demographics	job_category
0	anonymous	0.0	Hispanic_or_Latino	Professionals
1	anonymous	0.0	Hispanic_or_Latino	Professionals
2	anonymous	0.8	Hispanic_or_Latino	Professionals
3	anonymous	1.3	Hispanic_or_Latino	Professionals
4	anonymous	1.6	Hispanic_or_Latino	Professionals

Although the set is rich in information, many company names are hidden and we do not have reference indices to group them by company. The set has been previously sorted, and the original data structure cannot be observed. Therefore, we will clean the data by eliminating all entries with company name 'anonymous.'

In [7]:
```
distribution_data = distribution_data_raw.loc[distribution_data_raw["company"]
 != "anonymous",]
distribution_data = distribution_data.sort_values(axis = 0, ascending = False,
 by = "company")
distribution_data.head(5)
```

Out[7]:

	company	percentage	demographics	job_category
19	eBay	2.6	Hispanic_or_Latino	Professionals
12691	eBay	12.0	Asian_female	Managers
9047	eBay	5.2	Underrepresented_minorities	Executives-Managers-Professionals
936	eBay	10.3	White_female	Professionals
9268	eBay	3.4	Hispanic_or_Latino	Executives and Managers

Let's see if the number of entries per company name, demographic categories, and job categories is uniform because that would indicate the remaining categories are standardized:

In [8]:
```
print(distribution_data['company'].value_counts())
```

```
HPE           91
NetApp        91
Nvidia        91
Google        91
LinkedIn      91
Salesforce    91
Intel         91
Adobe         91
Intuit        91
Facebook      91
View          91
Pinterest     91
PayPal        91
HP Inc.       91
23andMe       91
Lyft          91
Airbnb        91
Apple         91
Uber          91
Cisco         91
Twitter       91
MobileIron    91
eBay          91
Sanmina       91
Square        91
Name: company, dtype: int64
```

In [9]:
```
print(distribution_data['demographics'].value_counts())
```

```
Underrepresented_minorities           175
Hispanic_or_Latino                    175
Asian                                 175
Women_of_color                        175
Asian_female                          175
Female_total                          175
Black_or_African_American_female      175
White_female                          175
Black_or_African_American             175
Underrepresented_minorities_female    175
White                                 175
Hispanic_or_Latino_female             175
People_of_color                       175
Name: demographics, dtype: int64
```

In [10]:
```
print(distribution_data['job_category'].value_counts())
```

```
Executives                                           325
Professionals                                        325
All Workers                                          325
Executives and Managers                              325
Executives-Managers-Professionals                    325
Managers                                             325
Sales workers/admin support/technicians and others    325
Name: job_category, dtype: int64
```

All the numbers are uniform -- we are good to go.

Exploring and Importing Financial Performance Data

Since the original dataset does not provide financial performance data associated with these corporate entities, we conducted our own research to get the 2016 financial performance metrics for most companies. Let's take a look at the dataset:

We used each companies financial statements from 2016, since that's the year the diversity data is from, and imported different line items into an excel spreadsheet. Using that financial data we calculated Net Margins, Gross Margins, Operating Margins, EBITDA Margins, Pre-Tax Margins. We used margins because it simplifies financial statements and neglects factors such as size when comparing multiple companies within the same sector.

In [11]:
```
sv_financials = pd.read_csv("C:/Users/weiti/Desktop/Freshman Fall/ECON-UB 232/
finalProject/siliconValleyFinacials.csv")
sv_financials
```

Out[11]:

	company	ownership	TTM_Net_Margins	TTM_Gross_Margins	TTM_Operating_Marg
0	Pinterest	private	NaN	NaN	NaN
1	Square	public	-10.40%	33.71%	-9.98%
2	MobileIron	public	-40.98%	81.36%	-40.97%
3	PayPal	public	12.92%	47.42%	14.63%
4	Nvidia	public	19.86%	57.84%	23.64%
5	HP Inc.	public	5.17%	18.41%	7.14%
6	Airbnb	private	NaN	NaN	NaN
7	Lyft	private	NaN	NaN	NaN
8	View	private	NaN	NaN	NaN
9	Uber	private	NaN	NaN	NaN
10	Adobe	public	19.96%	86.60%	25.51%
11	Intuit	public	20.59%	25.43%	83.84%
12	Cisco	public	21.73%	63.40%	25.47%
13	HPE	public	10.44%	32.28%	12.89%
14	Facebook	public	36.86%	86.29%	44.90%
15	Google	public	22.29%	61.81%	26.25%
16	NetApp	public	5.89%	8.59%	61.09%
17	Apple	public	21.19%	29.08%	27.84%
18	Salesforce	public	2.60%	1.37%	74.98%
19	Sanmina	public	3.08%	7.84%	3.44%
20	eBay	public	80.92%	77.65%	25.89%
21	23andMe	private	NaN	NaN	NaN
22	Twitter	public	-18.06%	63.15%	-14.52%
23	Intel	public	17.37%	60.94%	21.68%
24	LinkedIn	public	NaN	NaN	NaN

Variable Breakdown for sv_finacial Data Frame

company: Name of the Company

year: 2016

ownership: refers to if the company is publicly or privately held -Possible Values: “private” or “public”

TTM_Net_Margins: company’s net-profit/revenue

TTM_Gross_Margins: company’s gross-profits/revenue

TTM_Operating_Margins: company’s operating-income/net-sales

EBITDA_Margins: company’s (earnings-before-interest, tax, depreciation and amortization) / total-revenue

Pre-Tax_Profit_Margins: company’s pre-tax-earnings/total sales

We filter out any private companies for they are not required to release their performance metrics. We are unable to evaluate LinkedIn's performance in 2016 becaue it was acquired by Microsoft in December, 2016, so we will apply `dropna` on the dataset along with a filter for public companies.

Moreover, the percentage figures in the chart above are string elements. We will convert them to floating point decimals for further calculation:

In [12]:
```
sv_public = sv_financials.loc[(sv_financials['ownership'] == "public"),].dropn
a()
sv_public['TTM_Net_Margins'] = (sv_public['TTM_Net_Margins'].str.replace("%",
"").astype(float))*0.01
sv_public['TTM_Gross_Margins'] = (sv_public['TTM_Gross_Margins'].str.replace(
"%","").astype(float))*0.01
sv_public['TTM_Operating_Margins'] = (sv_public['TTM_Operating_Margins'].str.r
eplace("%","").astype(float))*0.01
sv_public['EBITDA_Margins'] = (sv_public['EBITDA_Margins'].str.replace("%","")
.astype(float))*0.01
sv_public['Pre-Tax_Profit_Margins'] = (sv_public['Pre-Tax_Profit_Margins'].str
.replace("%","").astype(float))*0.01
sv_public
```

Out[12]:

	company	ownership	TTM_Net_Margins	TTM_Gross_Margins	TTM_Operating_Marg
1	Square	public	-0.1040	0.3371	-0.0998
2	MobileIron	public	-0.4098	0.8136	-0.4097
3	PayPal	public	0.1292	0.4742	0.1463
4	Nvidia	public	0.1986	0.5784	0.2364
5	HP Inc.	public	0.0517	0.1841	0.0714
10	Adobe	public	0.1996	0.8660	0.2551
11	Intuit	public	0.2059	0.2543	0.8384
12	Cisco	public	0.2173	0.6340	0.2547
13	HPE	public	0.1044	0.3228	0.1289
14	Facebook	public	0.3686	0.8629	0.4490
15	Google	public	0.2229	0.6181	0.2625
16	NetApp	public	0.0589	0.0859	0.6109
17	Apple	public	0.2119	0.2908	0.2784
18	Salesforce	public	0.0260	0.0137	0.7498
19	Sanmina	public	0.0308	0.0784	0.0344
20	eBay	public	0.8092	0.7765	0.2589
22	Twitter	public	-0.1806	0.6315	-0.1452
23	Intel	public	0.1737	0.6094	0.2168

Let's check the column data types:

In [13]:
```
sv_public.dtypes
```

Out[13]:
```
company                     object
ownership                   object
TTM_Net_Margins            float64
TTM_Gross_Margins          float64
TTM_Operating_Margins      float64
EBITDA_Margins             float64
Pre-Tax_Profit_Margins     float64
dtype: object
```

The company financial data is good to go. As a side note, although we will primarily conduct our analysis with the EBITDA measure for its reputation as an excellent performance metric, we keep other columns for potential reference.

Part I: Examine correlation between racial diversity and profitability in Silicon Valley companies

Previously when we explored the company-specific diversity dataset, we realize that the dataset included both racial and gender information within the same column. For Part I, we will only analyze the racial information, so let's first determine the criteria. We will only examine the company-wide percentages of White, Black or African American, Asian, and Hispanic or Latino employees at different job levels for simplicity's sake. We will filter out gender categorization for this part. We determine the criteria to be:

In [14]:
```
race_condition = ((distribution_data['demographics'] != "Underrepresented_mino
rities") &
                (distribution_data['demographics'] != "People_of_color") &
                (distribution_data['demographics'].str.lower().str.find('femal
e') == -1) &
                (distribution_data['demographics'].str.lower().str.find('wome
n') == -1))
```

Now we will filter the data based on our criteria, sort the data by company, job category, and demographics, and check our work:

When cleaning the data, we noticed that the data set contained racial categories that overlapped with each other or grouped many different races under one category. In order to make sure the overlapping data didn’t skew our final results, we decided to take out underrepresented minorities, as well as people of color since the races in those groups, such as Black, Asian, and have their own individual categories.

In [15]:
```
distribution_data_filtered = distribution_data.loc[race_condition,]
distribution_data_filtered = distribution_data_filtered.sort_values(by = ["com
pany","job_category","demographics"],
                                                                    axis = 0)
distribution_data_filtered['demographics'].value_counts()
```

Out[15]:
```
Hispanic_or_Latino           175
Black_or_African_American    175
White                        175
Asian                        175
Name: demographics, dtype: int64
```

It is a good sign that the numbers are uniform. Let's examine the job categories:

In [16]:
```
np.unique(distribution_data_filtered['job_category'])
```

Out[16]:
```
array(['All Workers', 'Executives', 'Executives and Managers',
       'Executives-Managers-Professionals', 'Managers', 'Professionals',
       'Sales workers/admin support/technicians and others'], dtype=object)
```

Everything seems good except for 'Sales workers/admin support/technicians and others.' Let's replace it with 'Others.' We will also change the percentage figures to their decimal forms and rename the 'percentage' column as 'proportion.'

In [17]:
```
label = "Sales workers/admin support/technicians and others"
distribution_data_filtered['job_category'] = distribution_data_filtered['job_c
ategory'].str.replace(label, "Others")
distribution_data_filtered['percentage'] = distribution_data_filtered['percent
age'] * 0.01
distribution_data_filtered = distribution_data_filtered.rename(columns = {'per
centage':'proportion'})
distribution_data_filtered.head(5)
```

Out[17]:

	company	proportion	demographics	job_category
5191	23andMe	0.236	Asian	All Workers
5001	23andMe	0.017	Black_or_African_American	All Workers
4707	23andMe	0.064	Hispanic_or_Latino	All Workers
4904	23andMe	0.626	White	All Workers
2854	23andMe	0.059	Asian	Executives

The racial diversity dataset is ready to go!

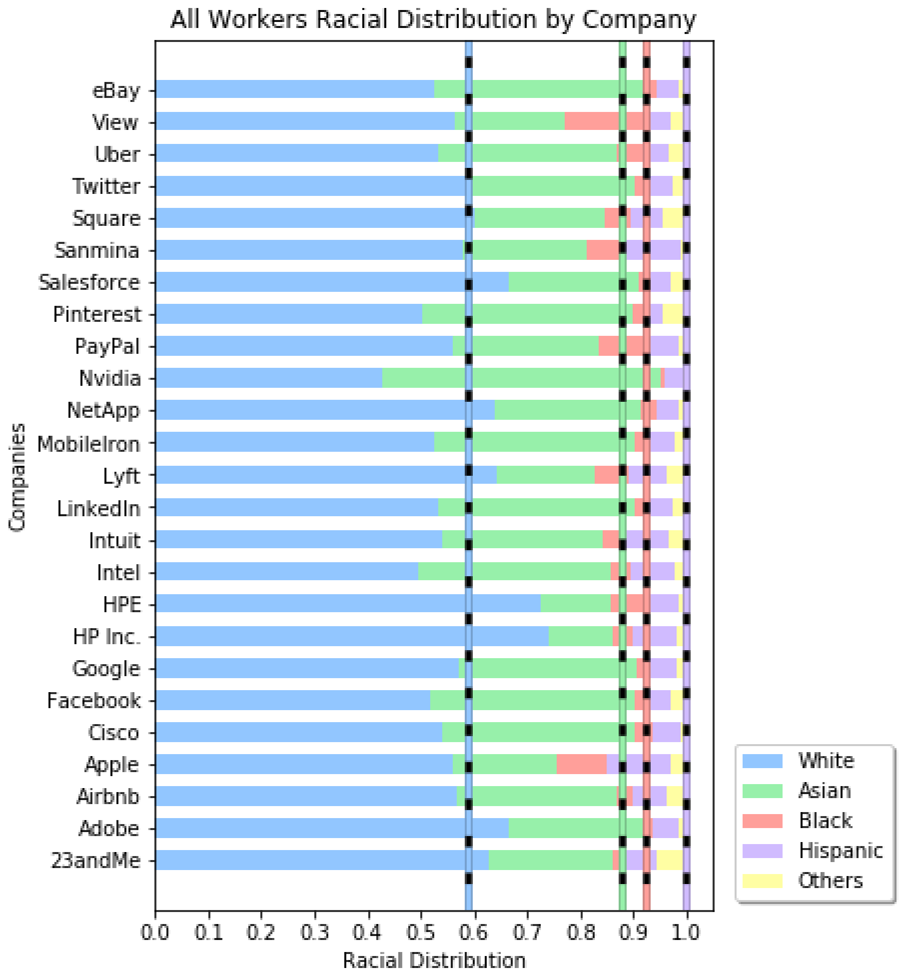
Racial Composition Overview: All Workers

In this section, we will overview each company's racial diversity through a stacked horizontal bar chart. The sector-wide proportion is denoted by vertical lines with corresponding colors for reference:

In [18]:
```
from matplotlib.patches import Rectangle
```

In [19]:
```
numCompanies = len(np.unique(distribution_data_filtered['company']))
ind = np.arange(numCompanies)
height = 0.6

allWorker_criteria = distribution_data_filtered['job_category'] == 'All Worker
s'

asianProp = list(distribution_data_filtered.loc[(distribution_data_filtered['d
emographics'] == 'Asian') &
                                                 allWorker_criteria,]['proporti
on'])
whiteProp = list(distribution_data_filtered.loc[(distribution_data_filtered['d
emographics'] == 'White') &
                                                 allWorker_criteria,]['proporti
on'])
blackProp = list(distribution_data_filtered.loc[(distribution_data_filtered['d
emographics'] == 'Black_or_African_American') &
                                                 allWorker_criteria,]['proporti
on'])
hispanicProp = list(distribution_data_filtered.loc[(distribution_data_filtered
['demographics'] == 'Hispanic_or_Latino') &
                                                   allWorker_criteria,]['propo
rtion'])
companies = list(np.unique(distribution_data_filtered['company']))

plt.style.use('seaborn-pastel')

plt.figure(figsize=(5,8))

white = plt.barh(y = ind, width = whiteProp, height = height)
asian = plt.barh(y = ind, width = asianProp, height = height,
                 left = whiteProp)
black = plt.barh(y = ind, width = blackProp, height = height,
                 left = [sum(x) for x in zip(asianProp, whiteProp)])
hispanic = plt.barh(y = ind, width = hispanicProp, height = height,
                    left = [sum(x) for x in zip(asianProp, whiteProp, blackPro
p)])
others = plt.barh(y = ind, width = [(1 - y) for y in [sum(x) for x in zip(asia
nProp, whiteProp, blackProp, hispanicProp)]],
                 height = height,
                 left = [sum(x) for x in zip(asianProp, whiteProp, blackProp,
hispanicProp)])

plt.ylabel('Companies')
plt.xlabel('Racial Distribution')
plt.title('All Workers Racial Distribution by Company')
plt.yticks(ind, companies)
plt.xticks(np.arange(0, 1.01, 0.1))
plt.legend((white[0], asian[0], black[0], hispanic[0], others[0]), ('White',
'Asian', 'Black', 'Hispanic', 'Others'),
          loc = 'lower left', bbox_to_anchor = (1.02, 0), shadow = True)

dist = 0
for race in [['White',white], ['Asian',asian], ['Black_or_African American',bl
ack], ['Hispanic_or_Latino', hispanic]]:
    bars = [r for r in race[1].get_children() if type(r) == Rectangle]
```

```
    colors = [c.get_facecolor() for c in bars[:-1]]
    dist = dist + float(race_overall.loc[race_overall['race_ethnicity'] == rac
e[0], 'percentage']*0.01)
    plt.axvline(dist, color = 'black', linestyle = '-', linewidth = 3.5)
    plt.axvline(dist, color = colors[1], linestyle = '--', linewidth = 3.5)

plt.show()
```



It seems like the racial diversity in Silicon Valley tech companies does not significantly differ from the sector average. Let's conduct a Chi-square Goodness-of-Fit test to affirm our observation, with the null hypothesis being that there exists no significant differences between the observed proportions and tech sector average proportions:

In [20]:
```
from scipy.stats import chisquare
```

In [21]:
```
exp_arr = [float(race_overall.loc[race_overall['race_ethnicity'] == 'White',
'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Asian',
'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Black_or_
African American', 'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Hispanic_
or_Latino', 'percentage']*0.01)]
```

In [22]:
```
chisquare(f_obs = np.array([whiteProp, asianProp, blackProp, hispanicProp]).T,
          f_exp = exp_arr)
```

Out[22]:
```
Power_divergenceResult(statistic=array([0.2184519 , 0.7117694 , 0.54233857,
0.24223842]), pvalue=array([1., 1., 1., 1.]))
```

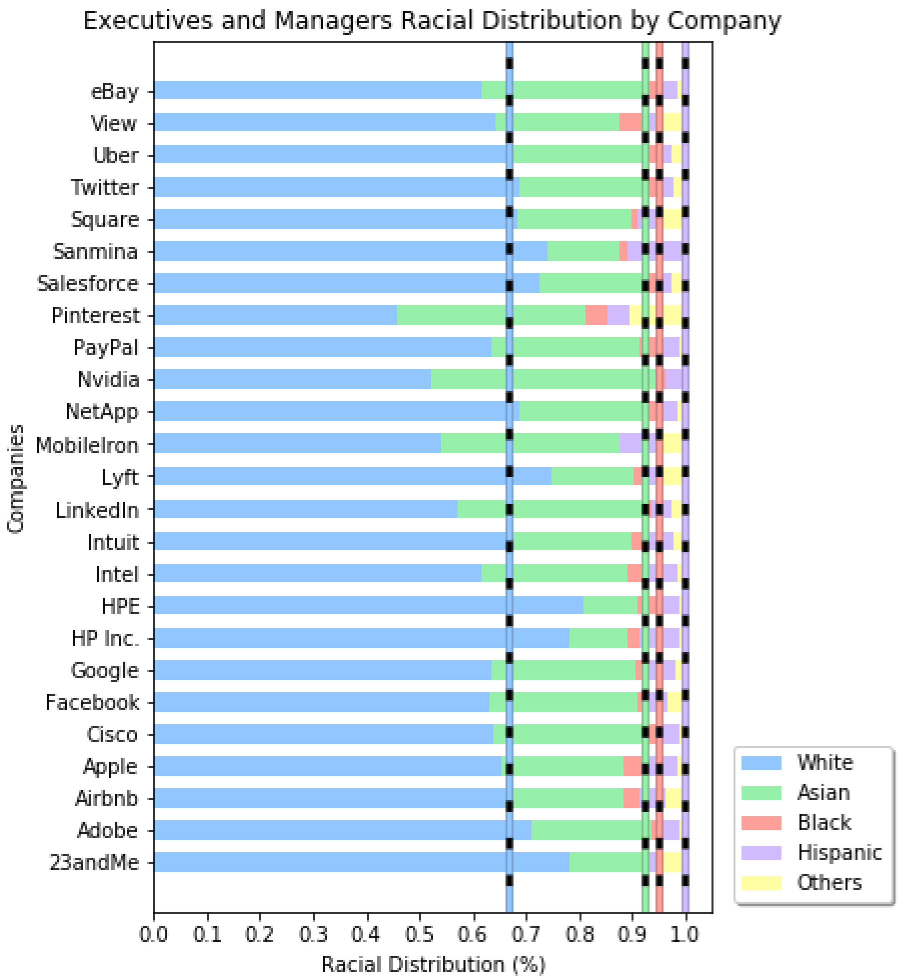
Since p-values all approximates to 1, we conclude that the Silicon Valley tech company's diversity data fits the those of the tech sector average.

Racial Composition Overview: Executives and Managers

We analyze the racial diversity among Silicon Valley employees that are managers and above through the same method:

In [23]:
```
numCompanies = len(np.unique(distribution_data_filtered['company']))
ind = np.arange(numCompanies)
height = 0.6

execMgmt_criteria = distribution_data_filtered['job_category'] == 'Executives
 and Managers'

asianProp = list(distribution_data_filtered.loc[(distribution_data_filtered['d
emographics'] == 'Asian') &
                                                execMgmt_criteria,]['proportio
n'])
whiteProp = list(distribution_data_filtered.loc[(distribution_data_filtered['d
emographics'] == 'White') &
                                                execMgmt_criteria,]['proportio
n'])
blackProp = list(distribution_data_filtered.loc[(distribution_data_filtered['d
emographics'] == 'Black_or_African_American') &
                                                execMgmt_criteria,]['proportio
n'])
hispanicProp = list(distribution_data_filtered.loc[(distribution_data_filtered
['demographics'] == 'Hispanic_or_Latino') &
                                                   execMgmt_criteria,]['propor
tion'])
companies = list(np.unique(distribution_data_filtered['company']))

plt.style.use('seaborn-pastel')

plt.figure(figsize=(5,8))

white = plt.barh(y = ind, width = whiteProp, height = height)
asian = plt.barh(y = ind, width = asianProp, height = height,
                 left = whiteProp)
black = plt.barh(y = ind, width = blackProp, height = height,
                 left = [sum(x) for x in zip(asianProp, whiteProp)])
hispanic = plt.barh(y = ind, width = hispanicProp, height = height,
                    left = [sum(x) for x in zip(asianProp, whiteProp,blackProp
)])
others = plt.barh(y = ind, width = [(1 - y) for y in [sum(x) for x in zip(asia
nProp, whiteProp, blackProp, hispanicProp)]],
                 height = height,
                 left = [sum(x) for x in zip(asianProp, whiteProp,blackProp, h
ispanicProp)])

plt.ylabel('Companies')
plt.xlabel('Racial Distribution (%)')
plt.title('Executives and Managers Racial Distribution by Company')
plt.yticks(ind, companies)
plt.xticks(np.arange(0, 1.01, 0.1))
plt.legend((white[0], asian[0], black[0], hispanic[0], others[0]), ('White',
'Asian', 'Black', 'Hispanic', 'Others'),
          loc = 'lower left', bbox_to_anchor = (1.02, 0), shadow = True)

dist = 0
for race in [['White',white], ['Asian',asian], ['Black_or_African American',bl
ack], ['Hispanic_or_Latino', hispanic]]:
    bars = [r for r in race[1].get_children() if type(r) == Rectangle]
```

```
    colors = [c.get_facecolor() for c in bars[:-1]]
    dist = dist + float(race_execmgmt.loc[race_execmgmt['race_ethnicity'] == r
ace[0], 'percentage']*0.01)
    plt.axvline(dist, color = 'black', linestyle = '-', linewidth = 3.5)
    plt.axvline(dist, color = colors[1], linestyle = '--', linewidth = 3.5)

plt.show()
```



Let's conduct a Chi-square Goodness-of-Fit test on this set of observations:

In [24]:
```
exp_arr = [float(race_execmgmt.loc[race_execmgmt['race_ethnicity'] == 'White',
 'percentage']*0.01),
           float(race_execmgmt.loc[race_execmgmt['race_ethnicity'] == 'Asian',
 'percentage']*0.01),
           float(race_execmgmt.loc[race_execmgmt['race_ethnicity'] == 'Black_o
r_African American', 'percentage']*0.01),
           float(race_execmgmt.loc[race_execmgmt['race_ethnicity'] == 'Hispani
c_or_Latino', 'percentage']*0.01)]
```

In [25]:
```
chisquare(f_obs = np.array([whiteProp, asianProp, blackProp, hispanicProp]).T,
          f_exp = exp_arr)
```

Out[25]:
```
Power_divergenceResult(statistic=array([0.24790875, 0.60116586, 0.12456069,
0.17175217]), pvalue=array([1., 1., 1., 1.]))
```

Since all p-values are close to 1, we conclude that the Silicon Valley tech companies' racial diversity data do not significantly differ from those of the tech industry on both all-worker and managers-and-above levels.

Examine correlation

After concluding that Silicon Valley tech companies are decent snapshots of the racial diversity situation across the tech industry, let's examine the correlation between racial diversity and company profitability (as measured by EBITDA margin). First, we design the **Racial Diversity Index** of a company to be:

$$RDI = \prod Proportion\ of\ Race\ i$$

, where we only consider the proportions of the races White, Asian, Black or African American, and Hispanic or Latino. We calculate these indicators for every job category for every company.

In [26]:
```
temp = pd.merge(distribution_data_filtered.loc[distribution_data_filtered['job
_category'] == "All Workers",]
                .groupby('company', as_index = False).agg({'proportion':np.pro
d}),
                distribution_data_filtered.loc[distribution_data_filtered['job
_category'] == "Executives",]
                .groupby('company', as_index = False).agg({'proportion':np.pro
d}), on = "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_filtered.loc[distribution_data_filtered['job
_category'] == "Managers",]
                .groupby('company', as_index = False).agg({'proportion':np.pro
d}), on = "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_filtered.loc[distribution_data_filtered['job
_category'] == "Professionals",]
                .groupby('company', as_index = False).agg({'proportion':np.pro
d}), on = "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_filtered.loc[distribution_data_filtered['job
_category'] == "Others",]
                .groupby('company', as_index = False).agg({'proportion':np.pro
d}), on = "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_filtered.loc[distribution_data_filtered['job
_category'] == "Executives and Managers",]
                .groupby('company', as_index = False).agg({'proportion':np.pro
d}), on = "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_filtered.loc[distribution_data_filtered['job
_category'] == "Executives-Managers-Professionals",]
                .groupby('company', as_index = False).agg({'proportion':np.pro
d}), on = "company", how = "inner")

racial_dist = temp
racial_dist.columns = ['company',
                       'ri_allWorkers',
                       'ri_executives',
                       'ri_managers',
                       'ri_professionals',
                       'ri_others',
                       'ri_exec_mgmt',
                       'ri_exec_mgmt_prof']

racial_dist
```

Out[26]:

	company	ri_allWorkers	ri_executives	ri_managers	ri_professionals	ri_others	ri_e
0	23andMe	0.000161	0.000000	0.000000	0.000281	0.000272	0.0(
1	Adobe	0.000128	0.000000	0.000092	0.000127	0.000142	0.0(
2	Airbnb	0.000324	0.000109	0.000253	0.000277	0.000324	0.0(
3	Apple	0.001238	0.000057	0.000356	0.000181	0.001048	0.0(
4	Cisco	0.000338	0.000081	0.000192	0.000345	0.000161	0.0(
5	Facebook	0.000205	0.000160	0.000121	0.000182	0.000382	0.0(
6	Google	0.000238	0.000000	0.000208	0.000177	0.000572	0.0(
7	HP Inc.	0.000276	0.000065	0.000153	0.000244	0.000282	0.0(
8	HPE	0.000382	0.000044	0.000138	0.000408	0.000365	0.0(
9	Intel	0.000564	0.000032	0.000315	0.000416	0.000772	0.0(
10	Intuit	0.000546	0.000029	0.000237	0.000245	0.000971	0.0(
11	LinkedIn	0.000231	0.000043	0.000141	0.000216	0.000153	0.0(
12	Lyft	0.000553	0.000000	0.000065	0.000412	0.000463	0.0(
13	MobileIron	0.000203	0.000000	0.000000	0.000219	0.000070	0.0(
14	NetApp	0.000230	0.000193	0.000151	0.000269	0.000070	0.0(
15	Nvidia	0.000076	0.000017	0.000154	0.000057	0.000375	0.0(
16	PayPal	0.000834	0.000142	0.000239	0.000262	0.000520	0.0(
17	Pinterest	0.000154	0.000000	0.000422	0.000160	0.000038	0.0(
18	Salesforce	0.000145	0.000000	0.000092	0.000173	0.000078	0.0(
19	Sanmina	0.000971	0.000057	0.000193	0.000397	0.001417	0.0(
20	Square	0.000425	0.000000	0.000092	0.000115	0.001120	0.0(
21	Twitter	0.000216	0.000000	0.000129	0.000204	0.000303	0.0(
22	Uber	0.000414	0.000033	0.000103	0.000159	0.001077	0.0(
23	View	0.000774	0.000000	0.000348	0.000230	0.000571	0.0(
24	eBay	0.000196	0.000102	0.000134	0.000045	0.000245	0.0(

Since RDI caps at 0.25^4 or approximately 0.0039, RIs are very small. To make them easier for visual assessment and better for modeling, let's standardize them by replacing them with their z-scores relative to their peers. Since this operation will be repeated quite a few times, we will construct a function:

In [27]:
```
def num_to_z_score(df):
    temp = df
    columnTypes = (df.dtypes == 'float64')
    columnNames = df.columns
    for i in range(0,temp.shape[1]):
        if(columnTypes[i]):
            mean = temp[columnNames[i]].mean()
            std = temp[columnNames[i]].std()
            temp[columnNames[i]] = (temp[columnNames[i]] - mean) / std
            temp = temp.rename(columns = {columnNames[i]:('z_'+columnNames[i
])})
    return(temp)
```

Let's apply the function on the racial distribution dataset:

In [28]:
```
racial_dist_z = num_to_z_score(racial_dist)
racial_dist_z
```

Out[28]:

	company	z_ri_allWorkers	z_ri_executives	z_ri_managers	z_ri_professionals	z_ri_
0	23andMe	-0.794395	-0.830288	-1.634144	0.470762	-0.51
1	Adobe	-0.905267	-0.830288	-0.768249	-1.015200	-0.85
2	Airbnb	-0.234714	1.117163	0.756169	0.439445	-0.38
3	Apple	2.890578	0.190027	1.730284	-0.494372	1.496
4	Cisco	-0.186829	0.615345	0.180531	1.089814	-0.80
5	Facebook	-0.641817	2.026414	-0.494981	-0.485243	-0.23
6	Google	-0.530466	-0.830288	0.326770	-0.531729	0.262
7	HP Inc.	-0.398967	0.323156	-0.189976	0.116543	-0.49
8	HPE	-0.037800	-0.047902	-0.333403	1.694031	-0.27
9	Intel	0.583912	-0.254352	1.341244	1.772385	0.779
10	Intuit	0.524722	-0.313913	0.605368	0.125148	1.297
11	LinkedIn	-0.555036	-0.070336	-0.300558	-0.155001	-0.82
12	Lyft	0.548058	-0.830288	-1.023990	1.739807	-0.02
13	MobileIron	-0.650895	-0.830288	-1.634144	-0.127516	-1.04
14	NetApp	-0.558032	2.615591	-0.211930	0.357161	-1.04
15	Nvidia	-1.084300	-0.519083	-0.182791	-1.691103	-0.25
16	PayPal	1.508625	1.701154	0.626914	0.287934	0.124
17	Pinterest	-0.815863	-0.830288	2.348846	-0.697408	-1.12
18	Salesforce	-0.847653	-0.830288	-0.765880	-0.567900	-1.02
19	Sanmina	1.978778	0.179892	0.187668	1.595890	2.458
20	Square	0.108451	-0.830288	-0.768278	-1.122678	1.686
21	Twitter	-0.605444	-0.830288	-0.414041	-0.272867	-0.43
22	Uber	0.071482	-0.243121	-0.659992	-0.706295	1.572
23	View	1.305178	-0.830288	1.649850	-0.022575	0.257
24	eBay	-0.672306	0.982845	-0.371287	-1.799033	-0.58

Exploring Correlations

Now that we have transformed the racial diversity indices, we will merge the ths RDI dataset with the financial performance set. The correlation matrix between standardized racial diversity index among different job categories and the financial performance indiactors is as the following:

In [29]:
```
combo_race = pd.merge(sv_public, racial_dist_z, on = "company", how = "inner")
racial_corr = combo_race.corr().drop(['TTM_Net_Margins',
                                      'TTM_Gross_Margins',
                                      'TTM_Operating_Margins',
                                      'EBITDA_Margins',
                                      'Pre-Tax_Profit_Margins'], axis = 1).hea
d(5)
racial_corr
```

Out[29]:

	z_ri_allWorkers	z_ri_executives	z_ri_managers	z_ri_professic
TTM_Net_Margins	-0.007294	0.394804	0.341269	-0.266237
TTM_Gross_Margins	-0.378992	-0.076391	-0.228785	-0.321885
TTM_Operating_Margins	-0.044428	0.308574	0.304048	-0.051791
EBITDA_Margins	0.084796	0.302399	0.546170	0.051723
Pre-Tax_Profit_Margins	0.064395	0.385875	0.502886	-0.148526

We are primarily interested in the correlation between EBITDA margin and Racial Diversity Indices. We observe that EBITDA margin has the highest correlation with RDI for managerial level and above (0.567233).

We chose to only go forward with analyzing EBITDA margins only because it encompasses data from all the other margins that we calculated. This means that EBITDA is a key representation of performance.

When comparing each companies Racial Diversity Index versus their EBITDA Margins we found that there was a strong positive correlation of .567 on the Executive and Manager level. The reason we think racial diversity has a positive correlation with regards to EBITDA opposed to lower level employees is the type of thinking the job requires. The work that professionals do is mostly following a set of given instructions and their creativity is limited within a set framework. In contrast, the executive level requires more of an innovative mindset because they are taking on more complex problems where there could be many ways to go about solving them. Having a unique perspective or a different way of thinking from the norm, which diversity provides, can allow companies to find more efficient solutions these than the traditional way.

Note: A .567 correlation by conventional standards isn't a high correlation. However, since there are many factors that contribute to a company's profitability, the fact that one of the individual factors is .567 means that is a strong indicator.

Multivariate Regression: Racial Distribution's Influence on Company Profitability

Let's conduct a multivariate linear regression with the explanatory variables as the Racial Diversity Indices at executive, manager, professional, and lower than professional levels of employees and the response variable as the EBITDA margin.

In [30]:
```
import statsmodels.api as sm
```

In [31]:
```
racial_factors = combo_race[['z_ri_executives', 'z_ri_managers','z_ri_professi
onals','z_ri_others']]
profitability = combo_race['EBITDA_Margins']

racial_factors = sm.add_constant(racial_factors)
est = sm.OLS(profitability, racial_factors).fit()

print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:          EBITDA_Margins   R-squared:                       0.42
9
Model:                             OLS   Adj. R-squared:                  0.25
3
Method:                  Least Squares   F-statistic:                     2.44
1
Date:                 Thu, 20 Dec 2018   Prob (F-statistic):             0.099
3
Time:                         13:14:48   Log-Likelihood:                 8.955
6
No. Observations:                   18   AIC:                            -7.91
1
Df Residuals:                       13   BIC:                            -3.45
9
Df Model:                            4

Covariance Type:             nonrobust

==============================================================================
=========
                         coef    std err          t      P>|t|      [0.025
   0.975]
------------------------------------------------------------------------------
---------
const                  0.2043      0.042      4.855      0.000       0.113
    0.295
z_ri_executives        0.0274      0.042      0.651      0.527      -0.063
    0.118
z_ri_managers          0.1852      0.068      2.742      0.017       0.039
    0.331
z_ri_professionals    -0.0291      0.042     -0.692      0.501      -0.120
    0.062
z_ri_others           -0.0581      0.050     -1.170      0.263      -0.165
    0.049
==============================================================================
=
Omnibus:                         0.073   Durbin-Watson:                   1.26
4
Prob(Omnibus):                   0.964   Jarque-Bera (JB):                0.06
2
Skew:                           -0.003   Prob(JB):                        0.96
9
Kurtosis:                        2.713   Cond. No.                         2.3
9
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

```
C:\Users\weiti\Anaconda3\lib\site-packages\scipy\stats\stats.py:1394: UserWar
ning: kurtosistest only valid for n>=20 ... continuing anyway, n=18
  "anyway, n=%i" % int(n))
```

When running a multilinear regression on our data we found that the Executive Manager level has the highest t-score and coefficient value. However, this test also suggests that diversity at the professional level actually decreases a company’s EBITDA. Further analyzing the data we see that there is a reason for this phenomenon. Again, professionals workload consists of very black and white tasks that don’t require creativity so the main upside of diversity isn’t applicable at this level. A Yale study [3] indicates that people are more comfortable working with people who are culturally similar to them because it means that they have similar ideas and interests. This is what might be the cause of the inefficiencies at the professional level since diversity is so heavily pushed. However, there is still an economically beneficial reason that companies still recruit for diversity for professionals. In order for the Executive and Manager level to be diverse, they need to have diversity programs for the professional level. People don’t come out of undergrad being executives, they are pulled out of the pool of professionals through promotion. So even though diversity at the professional level hurts a companies EBITDA, they to hire them at this level on at the executive level. The data also suggests that diversity at the Executive and Manager Level increases EBITDA more than the Professional level decreases it, so there is an overall net gain.

Part II: Examine correlation between gender diversity and profitability in Silicon Valley companies

We repeat the same data organization and cleaning procedure used to conduct analysis on the relationship between racial diversity and company profitability in Silicon Valley tech companies.

In [32]:
```
distribution_data_gender = distribution_data.loc[distribution_data['demographi
cs'] == 'Female_total',]
distribution_data_gender = distribution_data_gender.sort_values(by = ["compan
y","job_category","demographics"], axis = 0)
distribution_data_gender['job_category'] = distribution_data_gender['job_categ
ory'].str.replace("Sales workers/admin support/technicians and others", "Other
s")
distribution_data_gender['percentage'] = distribution_data_gender['percentage'
] * 0.01
distribution_data_gender = distribution_data_gender.rename(columns = {'percent
age':'proportion'})
distribution_data_gender.head(5)
```

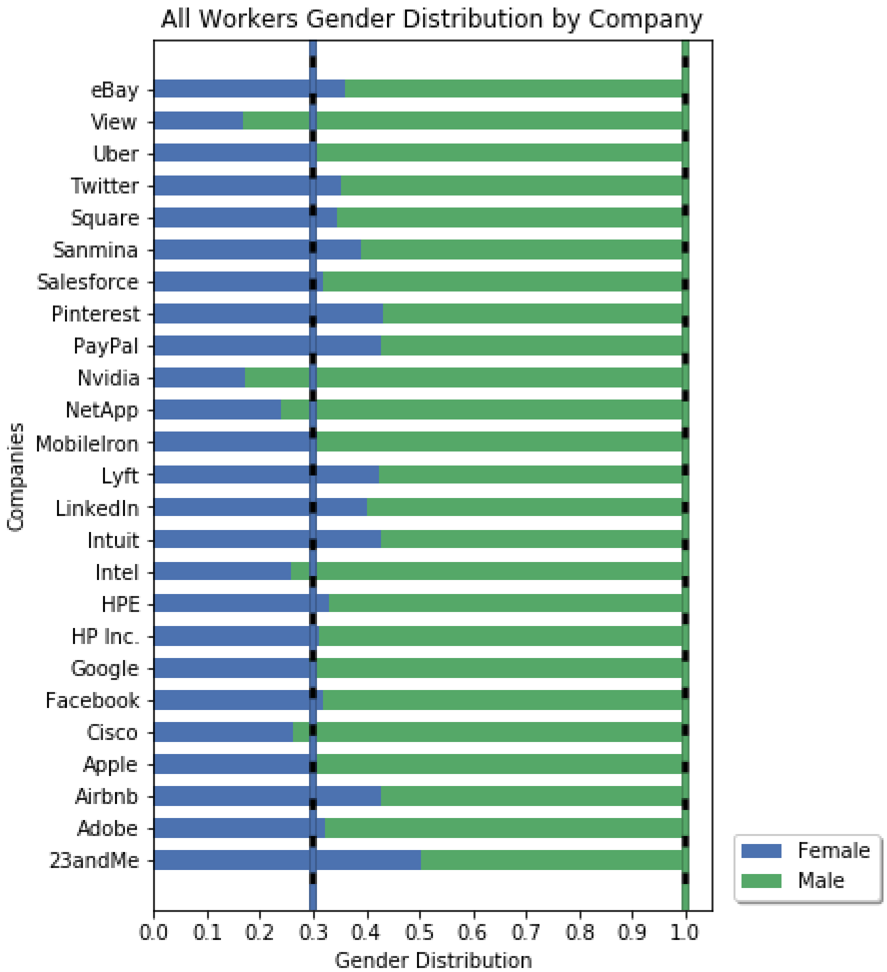
Out[32]:

	company	proportion	demographics	job_category
5475	23andMe	0.502	Female_total	All Workers
3183	23andMe	0.471	Female_total	Executives
10077	23andMe	0.451	Female_total	Executives and Managers
7769	23andMe	0.430	Female_total	Executives-Managers-Professionals
12359	23andMe	0.446	Female_total	Managers

Gender Composition Overview: All Workers

Similar to the corresponding section in racial diversity analysis, the vertical lines represent the corresponding sector average.

In [33]:
```
numCompanies = len(np.unique(distribution_data_gender['company']))
ind = np.arange(numCompanies)
height = 0.6

allWorker_criteria = distribution_data_gender['job_category'] == 'All Workers'

femaleProp = list(distribution_data_gender.loc[allWorker_criteria,]['proportio
n'])
maleProp = [(1 - x) for x in femaleProp]
companies = list(np.unique(distribution_data_gender['company']))

plt.style.use('seaborn-deep')

plt.figure(figsize=(5,8))

female = plt.barh(y = ind, width = femaleProp, height = height)
male = plt.barh(y = ind, width = maleProp, height = height, left = femaleProp)

plt.ylabel('Companies')
plt.xlabel('Gender Distribution')
plt.title('All Workers Gender Distribution by Company')
plt.yticks(ind, companies)
plt.xticks(np.arange(0, 1.01, 0.1))
plt.legend((female[0], male[0]), ('Female', 'Male'),
          loc = 'lower left', bbox_to_anchor = (1.02, 0), shadow = True)

dist = 0
for gender in [['Female',female], ['Male',male]]:
    bars = [g for g in gender[1].get_children() if type(g) == Rectangle]
    colors = [c.get_facecolor() for c in bars[:-1]]
    dist = dist + float(gender_overall.loc[gender_overall['gender'] == gender[
0], 'percentage']*0.01)
    plt.axvline(dist, color = 'black', linestyle = '-', linewidth = 3.5)
    plt.axvline(dist, color = colors[1], linestyle = '--', linewidth = 3.5)

plt.show()
```



Let's conduct a Chi-square Goodness-of-Fit test on this set of observations:

In [34]:
```
exp_arr = [float(gender_overall.loc[gender_overall['gender'] == 'Female', 'per
centage']*0.01),
           float(gender_overall.loc[gender_overall['gender'] == 'Male', 'perce
ntage']*0.01)]
```

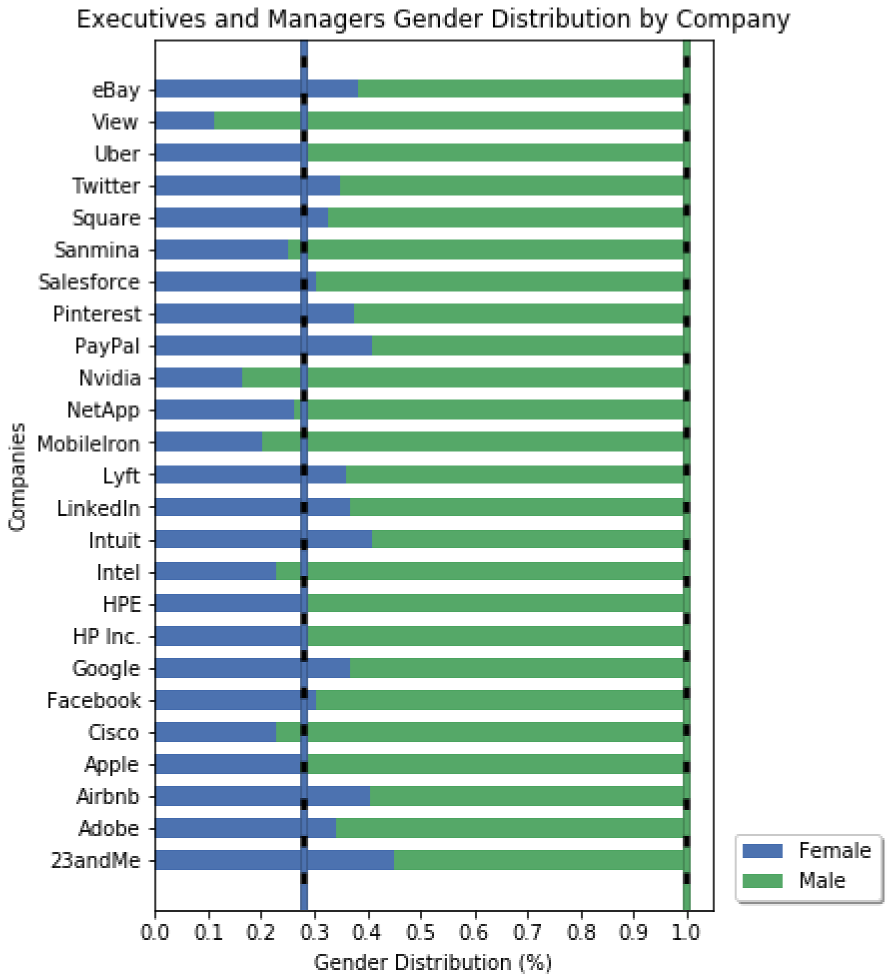
In [35]:
```
chisquare(f_obs = np.array([femaleProp, maleProp]).T,
          f_exp = exp_arr)
```

Out[35]:
```
Power_divergenceResult(statistic=array([0.63980503, 0.27469278]), pvalue=arra
y([1., 1.]))
```

Since all p-values are close to 1, we conclude that the Silicon Valley tech companies' gender diversity data do not significantly differ from those of the tech industry on all-worker level.

Gender Composition Overview: Executives and Managers

In [36]:
```
numCompanies = len(np.unique(distribution_data_gender['company']))
ind = np.arange(numCompanies)
height = 0.6

allWorker_criteria = distribution_data_gender['job_category'] == 'Executives a
nd Managers'

femaleProp = list(distribution_data_gender.loc[allWorker_criteria,]['proportio
n'])
maleProp = [(1 - x) for x in femaleProp]
companies = list(np.unique(distribution_data_gender['company']))

plt.style.use('seaborn-deep')

plt.figure(figsize=(5,8))

female = plt.barh(y = ind, width = femaleProp, height = height)
male = plt.barh(y = ind, width = maleProp, height = height, left = femaleProp)

plt.ylabel('Companies')
plt.xlabel('Gender Distribution (%)')
plt.title('Executives and Managers Gender Distribution by Company')
plt.yticks(ind, companies)
plt.xticks(np.arange(0, 1.01, 0.1))
plt.legend((female[0], male[0]), ('Female', 'Male'),
          loc = 'lower left', bbox_to_anchor = (1.02, 0), shadow = True)

dist = 0
for gender in [['Female',female], ['Male',male]]:
    bars = [g for g in gender[1].get_children() if type(g) == Rectangle]
    colors = [c.get_facecolor() for c in bars[:-1]]
    dist = dist + float(gender_execmgmt.loc[gender_execmgmt['gender'] == gende
r[0], 'percentage']*0.01)
    plt.axvline(dist, color = 'black', linestyle = '-', linewidth = 3.5)
    plt.axvline(dist, color = colors[1], linestyle = '--', linewidth = 3.5)

plt.show()
```



Let's conduct a Chi-square Goodness-of-Fit test on this set of observations:

In [37]:
```
exp_arr = [float(gender_execmgmt.loc[gender_execmgmt['gender'] == 'Female', 'p
ercentage']*0.01),
           float(gender_execmgmt.loc[gender_execmgmt['gender'] == 'Male', 'per
centage']*0.01)]
```

In [38]:
```
chisquare(f_obs = np.array([femaleProp, maleProp]).T,
          f_exp = exp_arr)
```

Out[38]:
```
Power_divergenceResult(statistic=array([0.65021368, 0.25545272]), pvalue=arra
y([1., 1.]))
```

Since all p-values are close to 1, we conclude that the Silicon Valley tech companies' gender diversity data do not significantly differ from those of the tech industry on both all-worker level and managers-and-above levels.

Examine Correlations

Similar procedure for racial diversity analysis. We define **Gender Index** for each company as:

$$GI = (Female\ Proportion) * (1 - Female\ Proportion)$$

, so we construct a column `GI` as the following:

In [39]:
```
distribution_data_gender['GI'] = distribution_data_gender['proportion']*(1-dis
tribution_data_gender['proportion'])
```

We repeat the procedure used for racial diversity analysis:

In [40]:
```
temp = pd.merge(distribution_data_gender.loc[distribution_data_gender['job_cat
egory'] == "All Workers",]
                .groupby('company', as_index = False).agg({'GI':np.prod}),
                distribution_data_gender.loc[distribution_data_gender['job_cat
egory'] == "Executives",]
                .groupby('company', as_index = False).agg({'GI':np.prod}), on
= "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_gender.loc[distribution_data_gender['job_cat
egory'] == "Managers",]
                .groupby('company', as_index = False).agg({'GI':np.prod}), on
= "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_gender.loc[distribution_data_gender['job_cat
egory'] == "Professionals",]
                .groupby('company', as_index = False).agg({'GI':np.prod}), on
= "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_gender.loc[distribution_data_gender['job_cat
egory'] == "Others",]
                .groupby('company', as_index = False).agg({'GI':np.prod}), on
= "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_gender.loc[distribution_data_gender['job_cat
egory'] == "Executives and Managers",]
                .groupby('company', as_index = False).agg({'GI':np.prod}), on
= "company", how = "inner")

temp = pd.merge(temp,
                distribution_data_gender.loc[distribution_data_gender['job_cat
egory'] == "Executives-Managers-Professionals",]
                .groupby('company', as_index = False).agg({'GI':np.prod}), on
= "company", how = "inner")

gender_dist = temp

gender_dist.columns = ['company',
                       'gi_allWorkers',
                       'gi_executives',
                       'gi_managers',
                       'gi_professionals',
                       'gi_others',
                       'gi_exec_mgmt',
                       'gi_exec_mgmt_prof']

gender_dist_z = num_to_z_score(gender_dist)
gender_dist_z
```

Out[40]:

	company	z_gi_allWorkers	z_gi_executives	z_gi_managers	z_gi_professionals	z_g
0	23andMe	1.144973	1.674208	1.109001	1.324714	-2.8
1	Adobe	0.055512	-0.251824	0.490435	-0.107990	0.1
2	Airbnb	0.971753	0.853109	1.091946	1.113016	0.6
3	Apple	-0.135866	-0.341759	-0.344673	-0.831883	0.1
4	Cisco	-0.802852	-0.114608	-1.036133	-0.734359	-0.(
5	Facebook	-0.006562	0.687084	0.095866	-0.124519	0.6
6	Google	-0.342720	-1.165181	0.679026	-1.178507	0.7
7	HP Inc.	-0.096353	0.373589	-0.172411	0.487210	-0.4
8	HPE	0.162910	-0.541325	-0.059130	0.419848	0.2
9	Intel	-0.835729	-1.119166	-1.019743	-0.490206	-0.8
10	Intuit	0.971753	0.785030	1.013377	0.963733	0.6
11	LinkedIn	0.814833	1.330015	0.663089	0.933450	0.7
12	Lyft	0.951670	-0.176356	0.694722	0.963733	0.6
13	MobileIron	-0.122626	-0.176356	-1.465504	0.902443	-1.2
14	NetApp	-1.179624	0.394428	-0.498401	-0.931418	-1.9
15	Nvidia	-2.554657	-1.384860	-1.465504	-2.958157	0.3
16	PayPal	0.971753	0.310076	0.989079	0.364511	0.6
17	Pinterest	0.981382	-1.227117	1.027231	1.241708	0.4
18	Salesforce	0.018474	0.342019	0.107367	0.279091	0.0
19	Sanmina	0.728997	-1.934868	-0.185300	0.565391	0.6
20	Square	0.329528	1.307764	0.262031	-0.058886	0.6
21	Twitter	0.412063	0.659500	0.571117	0.021345	0.5
22	Uber	-0.300111	0.574505	-0.358346	-0.563882	0.6
23	View	-2.599914	-1.831504	-2.979999	-1.459257	-1.9
24	eBay	0.461412	0.973597	0.790859	-0.141129	0.7

Gender Analysis: Exploring Correlations

Let's generate the correlation matrix as we did before:

In [41]:
```
combo_gender = pd.merge(sv_public, gender_dist_z, on = "company", how = "inne
r")
gender_corr = combo_gender.corr().drop(['TTM_Net_Margins',
                                        'TTM_Gross_Margins',
                                        'TTM_Operating_Margins',
                                        'EBITDA_Margins',
                                        'Pre-Tax_Profit_Margins'], axis = 1).h
ead(5)
gender_corr
```

Out[41]:

	z_gi_allWorkers	z_gi_executives	z_gi_managers	z_gi_profess
TTM_Net_Margins	-0.018305	0.073207	0.327118	-0.278619
TTM_Gross_Margins	-0.113082	0.037220	-0.059709	-0.170750
TTM_Operating_Margins	-0.065846	0.154047	0.281407	-0.124062
EBITDA_Margins	-0.071490	-0.099347	0.311441	-0.303710
Pre-Tax_Profit_Margins	-0.190994	-0.096618	0.205158	-0.433157

We observe that the correlation is still the highest between gender indeces of manager level and above and EBITDA margin, same as our conclusion for racial diversity analysis.

While there is still a correlation between EBITDA and gender diversity, it is much lower than the correlation between EBITDA and racial diversity. One of the reasons we think the results show this conclusion is because gender diversity doesn’t necessarily constitute that there are people from different cultures. There could be a lot of women from one race which means a high gender diversity but they are all influenced by the same culture. The argument for diversity is that it brings together many people from many different cultures in order to foster more efficient solutions. However, gender diversity doesn’t always 100% fit this argument which is evident in the example above.

Multivariate Regression: Gender Distribution's Influence on Company Profitability (EBITDA)

We conduct a multivariate regression in the same fashion:

In [42]:
```
gender_factors = combo_gender[['z_gi_executives', 'z_gi_managers','z_gi_profes
sionals','z_gi_others']]
profitability = combo_gender['EBITDA_Margins']

gender_factors = sm.add_constant(gender_factors)
est = sm.OLS(profitability, gender_factors).fit()

print(est.summary())
```

```
                            OLS Regression Results
==============================================================================
=
Dep. Variable:          EBITDA_Margins   R-squared:                       0.34
7
Model:                             OLS   Adj. R-squared:                  0.14
6
Method:                  Least Squares   F-statistic:                     1.72
8
Date:                 Thu, 20 Dec 2018   Prob (F-statistic):              0.20
4
Time:                         13:14:50   Log-Likelihood:                 7.750
6
No. Observations:                   18   AIC:                            -5.50
1
Df Residuals:                       13   BIC:                            -1.04
9
Df Model:                            4

Covariance Type:             nonrobust

==============================================================================
=========
                        coef    std err          t      P>|t|      [0.025
   0.975]
------------------------------------------------------------------------------
---------
const                 0.1809      0.045      3.992      0.002       0.083
    0.279
z_gi_executives      -0.0420      0.061     -0.692      0.501      -0.173
    0.089
z_gi_managers         0.1389      0.092      1.506      0.156      -0.060
    0.338
z_gi_professionals   -0.0987      0.056     -1.760      0.102      -0.220
    0.022
z_gi_others           0.0147      0.081      0.183      0.858      -0.159
    0.189
==============================================================================
=
Omnibus:                         1.297   Durbin-Watson:                   1.25
2
Prob(Omnibus):                   0.523   Jarque-Bera (JB):                0.82
5
Skew:                            0.010   Prob(JB):                        0.66
2
Kurtosis:                        1.951   Cond. No.                         3.2
6
==============================================================================
=

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correc
tly specified.
```

```
C:\Users\weiti\Anaconda3\lib\site-packages\scipy\stats\stats.py:1394: UserWar
ning: kurtosistest only valid for n>=20 ... continuing anyway, n=18
  "anyway, n=%i" % int(n))
```

The regression affirms our assumption that racial diversity is more impactful on EBITDA than gender diversity since none of the T-score values are significant.

Part III: Does gender diversity imply racial diversity?

We repeat the same data organization and cleaning procedure used to conduct analysis on the relationship between racial diversity and company profitability in Silicon Valley tech companies.

In [43]:

```
distribution_woman_race = distribution_data.loc[(distribution_data['demographi
cs'].str.find('female') > -1)&
                                                (distribution_data['demographi
cs'] != 'Underrepresented_minorities_female'),]
distribution_woman_race = distribution_woman_race.sort_values(by = ["company",
"job_category","demographics"], axis = 0)
distribution_woman_race['job_category'] = distribution_woman_race['job_categor
y'].str.replace("Sales workers/admin support/technicians and others", "Others"
)
distribution_woman_race['percentage'] = distribution_woman_race['percentage']
* 0.01
distribution_woman_race = distribution_woman_race.rename(columns = {'percentag
e':'proportion'}).reset_index()
distribution_woman_race.head(5)
```

Out[43]:

	index	company	proportion	demographics	job_category
0	5799	23andMe	0.131	Asian_female	All Workers
1	5938	23andMe	0.010	Black_or_African_American_female	All Workers
2	6166	23andMe	0.037	Hispanic_or_Latino_female	All Workers
3	5651	23andMe	0.283	White_female	All Workers
4	3493	23andMe	0.059	Asian_female	Executives

In [44]:

```
import math
```

In [45]:
```
woman_race_total = distribution_woman_race.groupby(['company','job_category'])
.agg({'proportion':np.sum})
distribution_woman_race['percentage'] = [distribution_woman_race['proportion']
[n]/
                                         woman_race_total['proportion'][math.c
eil((n+1)/4)-1]
                                         for n in range(0, len(distribution_wo
man_race['proportion']))]
distribution_woman_race.head(5)
```

```
C:\Users\weiti\Anaconda3\lib\site-packages\ipykernel_launcher.py:4: RuntimeWa
rning: invalid value encountered in double_scalars
  after removing the cwd from sys.path.
```

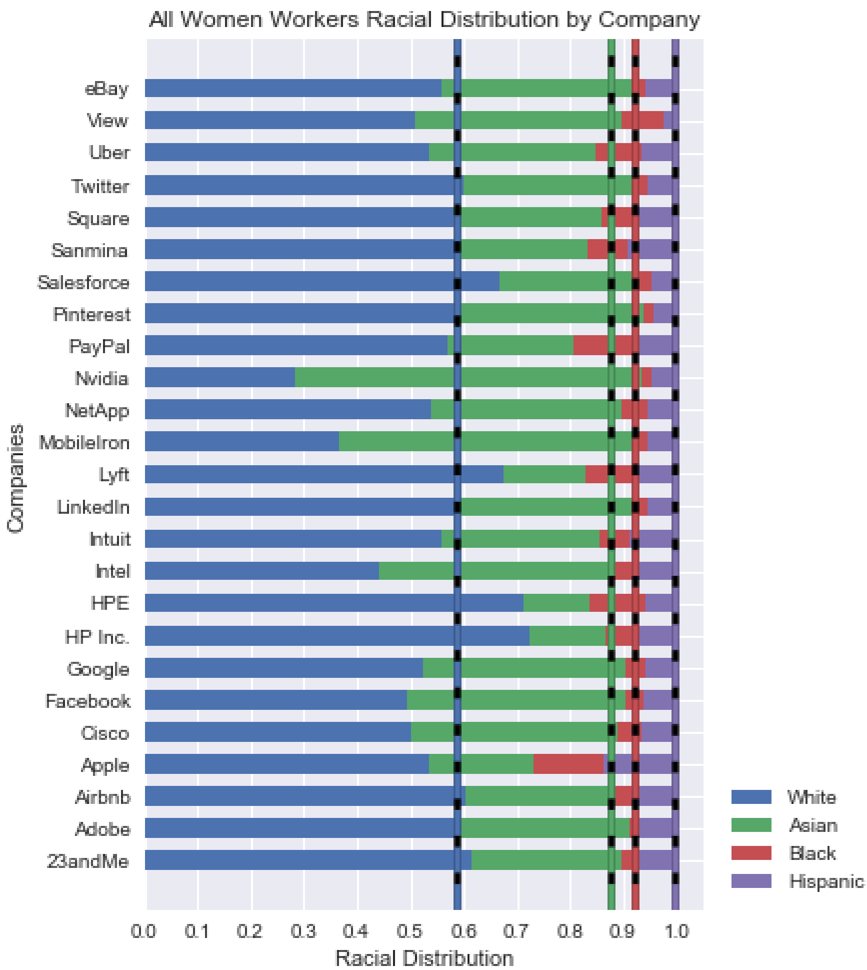
Out[45]:

	index	company	proportion	demographics	job_category	percenta
0	5799	23andMe	0.131	Asian_female	All Workers	0.284165
1	5938	23andMe	0.010	Black_or_African_American_female	All Workers	0.021692
2	6166	23andMe	0.037	Hispanic_or_Latino_female	All Workers	0.080260
3	5651	23andMe	0.283	White_female	All Workers	0.613883
4	3493	23andMe	0.059	Asian_female	Executives	0.125265

Women Racial Diveristy Composition Overview: All Workers

Similar to the corresponding section in racial diversity analysis, the vertical lines represent the corresponding sector average.

In [46]:
```
numCompanies = len(np.unique(distribution_woman_race['company']))
ind = np.arange(numCompanies)
height = 0.6

allWorker_criteria = distribution_woman_race['job_category'] == 'All Workers'

asianProp = list(distribution_woman_race.loc[(distribution_woman_race['demogra
phics'].str.find('Asian') > -1) &
                                              allWorker_criteria,]['percenta
ge'])
whiteProp = list(distribution_woman_race.loc[(distribution_woman_race['demogra
phics'].str.find('White') > -1) &
                                              allWorker_criteria,]['percenta
ge'])
blackProp = list(distribution_woman_race.loc[(distribution_woman_race['demogra
phics'].str.find('Black') > -1) &
                                              allWorker_criteria,]['percenta
ge'])
hispanicProp = list(distribution_woman_race.loc[(distribution_woman_race['demo
graphics'].str.find('Hispanic') > -1) &
                                                 allWorker_criteria,]['perce
ntage'])
companies = list(np.unique(distribution_woman_race['company']))

plt.style.use('seaborn')

plt.figure(figsize=(5,8))

white = plt.barh(y = ind, width = whiteProp, height = height)
asian = plt.barh(y = ind, width = asianProp, height = height,
                 left = whiteProp)
black = plt.barh(y = ind, width = blackProp, height = height,
                 left = [sum(x) for x in zip(asianProp, whiteProp)])
hispanic = plt.barh(y = ind, width = hispanicProp, height = height,
                    left = [sum(x) for x in zip(asianProp, whiteProp, blackPro
p)])

plt.ylabel('Companies')
plt.xlabel('Racial Distribution')
plt.title('All Women Workers Racial Distribution by Company')
plt.yticks(ind, companies)
plt.xticks(np.arange(0, 1.01, 0.1))
plt.legend((white[0], asian[0], black[0], hispanic[0]), ('White', 'Asian', 'Bl
ack', 'Hispanic'),
          loc = 'lower left', bbox_to_anchor = (1.02, 0), shadow = True)

dist = 0
for race in [['White',white], ['Asian',asian], ['Black_or_African American',bl
ack], ['Hispanic_or_Latino', hispanic]]:
    bars = [r for r in race[1].get_children() if type(r) == Rectangle]
    colors = [c.get_facecolor() for c in bars[:-1]]
    dist = dist + float(race_overall.loc[race_overall['race_ethnicity'] == rac
e[0], 'percentage']*0.01)
    plt.axvline(dist, color = 'black', linestyle = '-', linewidth = 3.5)
    plt.axvline(dist, color = colors[1], linestyle = '--', linewidth = 3.5)
```



Let's conduct a Chi-square Goodness-of-Fit test on this set of observations:

In [47]:
```
exp_arr = [float(race_overall.loc[race_overall['race_ethnicity'] == 'White',
'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Asian',
'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Black_or_
African American', 'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Hispanic_
or_Latino', 'percentage']*0.01)]
```

In [48]:
```
chisquare(f_obs = np.array([whiteProp, asianProp, blackProp, hispanicProp]).T,
          f_exp = exp_arr)
```

Out[48]:
```
Power_divergenceResult(statistic=array([0.43155695, 1.26662417, 0.61266485,
0.17562999]), pvalue=array([1., 1., 1., 1.]))
```

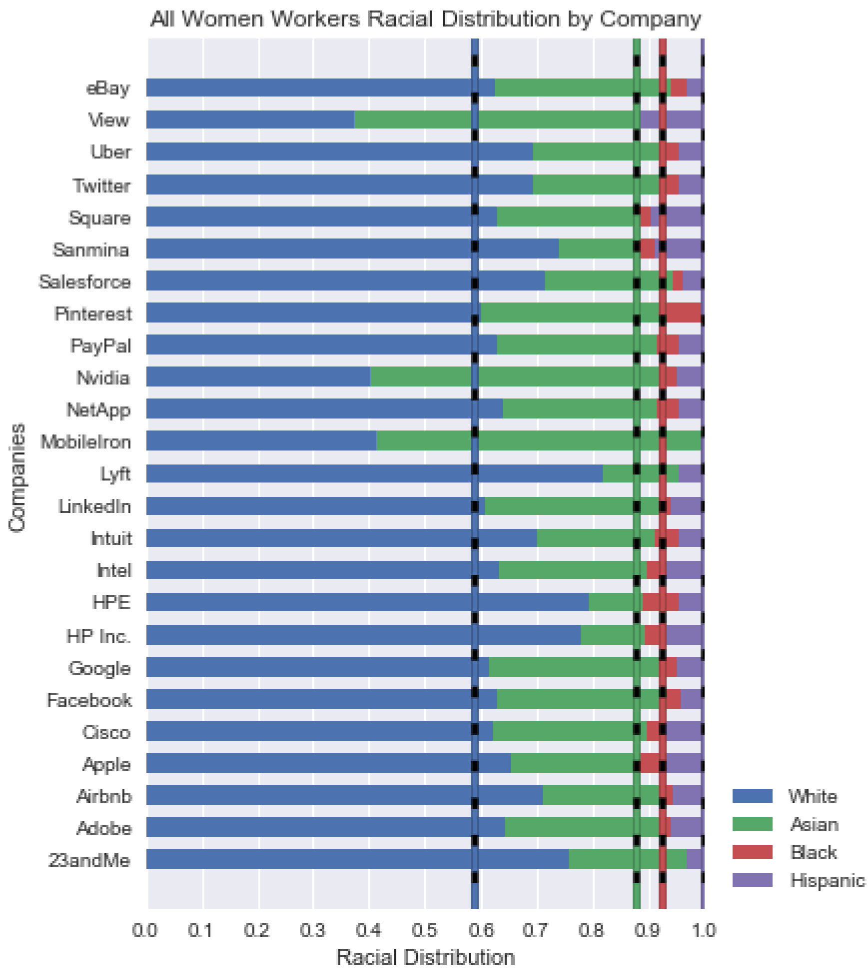
Since all p-values are close to 1, we conclude that the Silicon Valley tech companies' gender diversity data do not significantly differ from those of the tech industry on all-worker level.

Women Racial Diveristy Composition Overview: Executives and Managers

Similar to the corresponding section in racial diversity analysis, the vertical lines represent the corresponding sector average.

In [49]:
```
numCompanies = len(np.unique(distribution_woman_race['company']))
ind = np.arange(numCompanies)
height = 0.6

execmgmt_criteria = distribution_woman_race['job_category'] == 'Executives and
 Managers'

asianProp = list(distribution_woman_race.loc[(distribution_woman_race['demogra
phics'].str.find('Asian') > -1) &
                                                execmgmt_criteria,]['percentag
e'])
whiteProp = list(distribution_woman_race.loc[(distribution_woman_race['demogra
phics'].str.find('White') > -1) &
                                                execmgmt_criteria,]['percentag
e'])
blackProp = list(distribution_woman_race.loc[(distribution_woman_race['demogra
phics'].str.find('Black') > -1) &
                                                execmgmt_criteria,]['percentag
e'])
hispanicProp = list(distribution_woman_race.loc[(distribution_woman_race['demo
graphics'].str.find('Hispanic') > -1) &
                                                   execmgmt_criteria,]['percen
tage'])
companies = list(np.unique(distribution_woman_race['company']))

plt.style.use('seaborn')

plt.figure(figsize=(5,8))

white = plt.barh(y = ind, width = whiteProp, height = height)
asian = plt.barh(y = ind, width = asianProp, height = height,
                 left = whiteProp)
black = plt.barh(y = ind, width = blackProp, height = height,
                 left = [sum(x) for x in zip(asianProp, whiteProp)])
hispanic = plt.barh(y = ind, width = hispanicProp, height = height,
                    left = [sum(x) for x in zip(asianProp, whiteProp, blackPro
p)])

plt.ylabel('Companies')
plt.xlabel('Racial Distribution')
plt.title('All Women Workers Racial Distribution by Company')
plt.yticks(ind, companies)
plt.xticks(np.arange(0, 1.01, 0.1))
plt.legend((white[0], asian[0], black[0], hispanic[0]), ('White', 'Asian', 'Bl
ack', 'Hispanic'),
          loc = 'lower left', bbox_to_anchor = (1.02, 0), shadow = True)

dist = 0
for race in [['White',white], ['Asian',asian], ['Black_or_African American',bl
ack], ['Hispanic_or_Latino', hispanic]]:
    bars = [r for r in race[1].get_children() if type(r) == Rectangle]
    colors = [c.get_facecolor() for c in bars[:-1]]
    dist = dist + float(race_overall.loc[race_overall['race_ethnicity'] == rac
e[0], 'percentage']*0.01)
    plt.axvline(dist, color = 'black', linestyle = '-', linewidth = 3.5)
    plt.axvline(dist, color = colors[1], linestyle = '--', linewidth = 3.5)
```

```
plt.show()
```



Let's conduct a Chi-square Goodness-of-Fit test on this set of observations:

In [50]:
```
exp_arr = [float(race_overall.loc[race_overall['race_ethnicity'] == 'White',
'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Asian',
'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Black_or_
African American', 'percentage']*0.01),
           float(race_overall.loc[race_overall['race_ethnicity'] == 'Hispanic_
or_Latino', 'percentage']*0.01)]
```

In [51]:
```
chisquare(f_obs = np.array([whiteProp, asianProp, blackProp, hispanicProp]).T,
          f_exp = exp_arr)
```

Out[51]:
```
Power_divergenceResult(statistic=array([0.63255458, 1.17152564, 0.36717048,
0.39317596]), pvalue=array([1., 1., 1., 1.]))
```

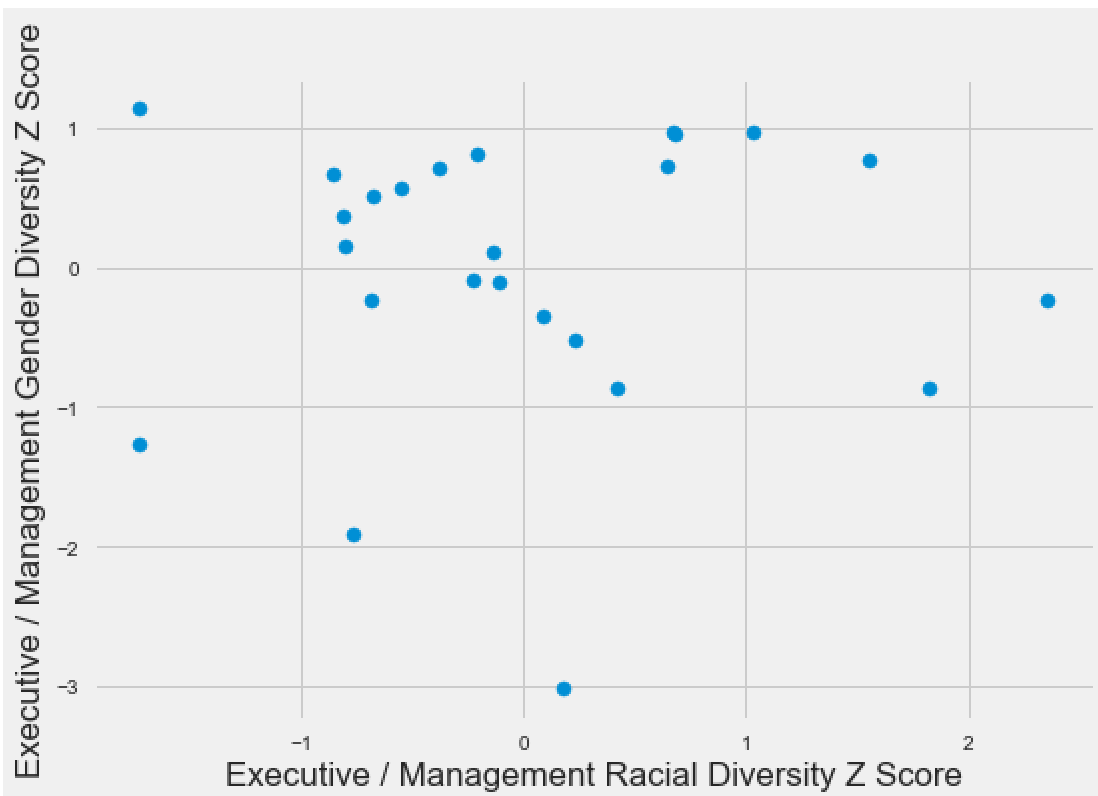
Since all p-values are close to 1, we conclude that the Silicon Valley tech companies' gender diversity data do not significantly differ from those of the tech industry on executive and management level.

Part IV: Explore clusters

For the last part of the project, we will explore company clusters formed by racial and gender indices at executives and management level and explore the profitability indicator in each cluster. To visualize our cluster findings, we will graph companies by their Executive / Management Racial Diversity Z Score (x) and their Executive / Management Gender Diversity Z Score (y):

In [52]:
```
plt.style.use('fivethirtyeight')

fig, ax = plt.subplots()
cluster_data = pd.merge(racial_dist_z[['company','z_ri_exec_mgmt']],
                        gender_dist_z[['company','z_gi_exec_mgmt']],
                        on = "company", how = "inner")
ax.scatter(x = cluster_data['z_ri_exec_mgmt'], y = cluster_data['z_gi_exec_mgm
t'])

ax.set_xlabel('Executive / Management Racial Diversity Z Score')
ax.set_ylabel('Executive / Management Gender Diversity Z Score')
```

Out[52]: `Text(0,0.5,'Executive / Management Gender Diversity Z Score')`



Now, let's import and apply the Agglomerative Clustering function from sklearn:

In [53]:
```
from sklearn.cluster import AgglomerativeClustering as aggCluster
```

In [54]:
```
cluster_data['cluster'] = aggCluster(n_clusters = 5).fit_predict(cluster_data.
set_index('company'))
cluster_data['cluster'] = [n + 1 for n in cluster_data['cluster']]
cluster_data = pd.merge(cluster_data, sv_public[['company','EBITDA_Margins']],
 on = "company", how = "inner")
cluster_data
```

Out[54]:

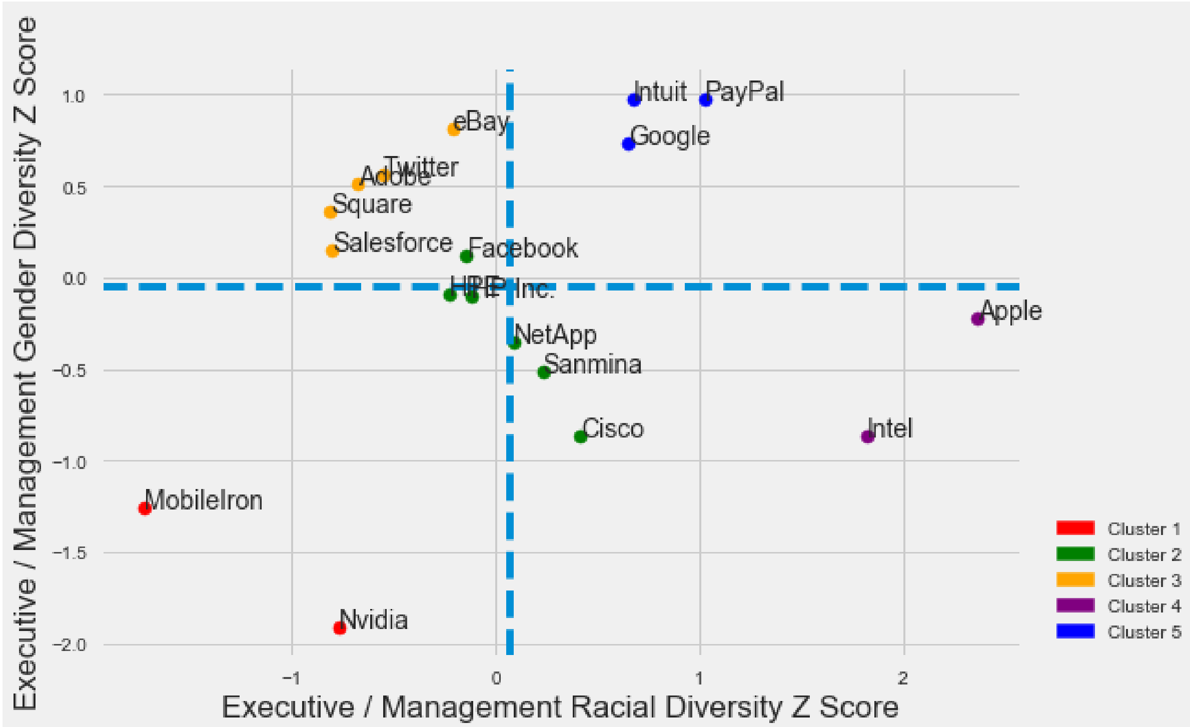
	company	z_ri_exec_mgmt	z_gi_exec_mgmt	cluster	EBITDA_Margins
0	Adobe	-0.676166	0.512443	3	0.3417
1	Apple	2.356307	-0.225748	4	0.3198
2	Cisco	0.417085	-0.864875	2	0.2952
3	Facebook	-0.139636	0.116740	2	0.4529
4	Google	0.648406	0.729274	5	0.3308
5	HP Inc.	-0.113427	-0.102369	2	0.0805
6	HPE	-0.229605	-0.090337	2	0.3536
7	Intel	1.818801	-0.864875	4	0.3581
8	Intuit	0.673591	0.976032	5	0.3043
9	MobileIron	-1.724489	-1.261551	1	-0.3780
10	NetApp	0.086527	-0.354685	2	0.1341
11	Nvidia	-0.767469	-1.912376	1	0.2111
12	PayPal	1.027858	0.970947	5	0.2131
13	Salesforce	-0.799967	0.149502	3	0.1362
14	Sanmina	0.231983	-0.516746	2	0.0518
15	Square	-0.811244	0.364832	3	-0.0772
16	Twitter	-0.552439	0.564129	3	0.0431
17	eBay	-0.209075	0.812638	3	0.3349

The after-clustering set is represented as the following:

In [55]:
```
import matplotlib.patches as mpatches
```

In [56]:
```
fig, ax = plt.subplots()
ax.scatter(cluster_data.loc[cluster_data['cluster'] == 0+1,'z_ri_exec_mgmt'],
           cluster_data.loc[cluster_data['cluster'] == 0+1,'z_gi_exec_mgmt'],
           color = 'red')
ax.scatter(cluster_data.loc[cluster_data['cluster'] == 1+1,'z_ri_exec_mgmt'],
           cluster_data.loc[cluster_data['cluster'] == 1+1,'z_gi_exec_mgmt'],
           color = 'green')
ax.scatter(cluster_data.loc[cluster_data['cluster'] == 2+1,'z_ri_exec_mgmt'],
           cluster_data.loc[cluster_data['cluster'] == 2+1,'z_gi_exec_mgmt'],
           color = 'orange')
ax.scatter(cluster_data.loc[cluster_data['cluster'] == 3+1,'z_ri_exec_mgmt'],
           cluster_data.loc[cluster_data['cluster'] == 3+1,'z_gi_exec_mgmt'],
           color = 'purple')
ax.scatter(cluster_data.loc[cluster_data['cluster'] == 4+1,'z_ri_exec_mgmt'],
           cluster_data.loc[cluster_data['cluster'] == 4+1,'z_gi_exec_mgmt'],
           color = 'blue')

ax.set_xlabel('Executive / Management Racial Diversity Z Score')
ax.set_ylabel('Executive / Management Gender Diversity Z Score')

for i in range(0, len(cluster_data)):
    ax.annotate(cluster_data.loc[i,'company'], (cluster_data.loc[i, 'z_ri_exec
_mgmt'],
                                                 cluster_data.loc[i, 'z_gi_exec
_mgmt']))

plt.axvline(cluster_data['z_ri_exec_mgmt'].mean(), linestyle = '--')
plt.axhline(cluster_data['z_gi_exec_mgmt'].mean(), linestyle = '--')

cluster0_patch = mpatches.Patch(color='red', label='Cluster 1')
cluster1_patch = mpatches.Patch(color='green', label='Cluster 2')
cluster2_patch = mpatches.Patch(color='orange', label='Cluster 3')
cluster3_patch = mpatches.Patch(color='purple', label='Cluster 4')
cluster4_patch = mpatches.Patch(color='blue', label='Cluster 5')
plt.legend(handles = [cluster0_patch, cluster1_patch, cluster2_patch, cluster3
_patch, cluster4_patch],
          loc = 'lower left', bbox_to_anchor = (1.02, 0), shadow = True)
```

Out[56]: <matplotlib.legend.Legend at 0x23460412dd8>



We have five clusters: the average in both indicator (2), the excellent in both (5), the underperforming in both (1), the excellent only for gender (3), and the excellent only for racial (4). Now, we will make boxplots to visualize and summarize the cluster profitability measures:

In [57]:
```
box_data = [0, 0, 0, 0, 0]
for n in np.unique(cluster_data['cluster'])-1:
    box_data[n] = cluster_data.loc[cluster_data['cluster'] == n+1,'EBITDA_Marg
ins']
fig, ax = plt.subplots()
bp = ax.boxplot(box_data)
ax.set_xlabel('Cluster')
ax.set_ylabel('EBITDA Margins')
ax.set_title('Clusters and Profitability')
```

Out[57]: Text(0.5,1,'Clusters and Profitability')

According to the visualization, Cluster 4 (the excellent only for racial) has the highest average profitability measure; however, we should take into account the fact that Cluster 4 only has two companies, making it much less an indicator of overall profitability of companies only excellent in racial diversity measures. Excluding cluster 4, the rest of the clusters shows that by being excellent in both measures (cluster 5) is better than being average in both measures (cluster 2), which is better than being excellent only in gender (cluster 3), which is better than being underperforming in both measures (cluster 1). This result affirms our previous conclusion that racial diversity may be more important in explaining company profitability and intellectual diversity because cluster 2 (average in both) is better than cluster 3 (excellent only in gender).

Conclusion

Through this project, we were able to show the relationship between racial and gender diversity on a company's EBITDA. We observed that racial diversity is much more correlated with a company's profitability measures, and we suggested that this is a result of the fact that diverse cultural experience and problem-solving approach are part of racial diversity, and people of different gender may have similar problem-solving approaches within the same race or culture. We further broke this problem down showing the impact of diversity on each level of employment. Though we had many interesting insights, the scope of the project was limited because we measured the success of a company purely on an economic register. There are many other ways to measure a company's success such as happiness of employees or philanthropic impact. Secondly, the sample size of our project was limited due to many companies not disclosing the gender and racial breakdown of their employees. Finally, correlation doesn't necessarily mean causation, so there is the possibility that diversity isn't directly related to the growth or decline of a company's profitability.

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GitHub Link

https://github.com/whong26/Data_Bootcamp (https://github.com/whong26/Data_Bootcamp)