In [17]:
```
import sys
!{sys.executable} -m pip install wordcloud
```

```
Collecting wordcloud
  Using cached wordcloud-1.8.1.tar.gz (220 kB)
Requirement already satisfied: numpy>=1.6.1 in /usr/local/lib/python3.8/site-packages (from wordcloud)
(1.19.4)
Requirement already satisfied: pillow in /usr/local/lib/python3.8/site-packages (from wordcloud) (8.0.
1)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.8/site-packages (from wordcloud)
(3.3.3)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.8/site-packages (from matplotlib
->wordcloud) (0.10.0)
Requirement already satisfied: python-dateutil>=2.1 in /usr/local/lib/python3.8/site-packages (from ma
tplotlib->wordcloud) (2.8.1)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.8/site-packages (from matpl
otlib->wordcloud) (1.3.1)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 in /usr/local/lib/python3.8/si
te-packages (from matplotlib->wordcloud) (2.4.7)
Requirement already satisfied: six in /usr/local/lib/python3.8/site-packages (from cycler>=0.10->matpl
otlib->wordcloud) (1.15.0)
Building wheels for collected packages: wordcloud
  Building wheel for wordcloud (setup.py) ... done
  Created wheel for wordcloud: filename=wordcloud-1.8.1-cp38-cp38-macosx_10_15_x86_64.whl size=160316
sha256=5f994285342d96d548d6c0f70e5f5a922d0c888fd301e182365ab2bf39e9a6e3
  Stored in directory: /Users/binayprasannajena/Library/Caches/pip/wheels/4d/3f/0d/a2ba9b7895c9f1be890
18b3141c3df3d4f9c786c882ccfbc3b
Successfully built wordcloud
Installing collected packages: wordcloud
Successfully installed wordcloud-1.8.1
```

In [18]:
```
import numpy as np
import pandas as pd
# data structures and operations for manipulating numerical tables and time series
import matplotlib.pyplot as plt
# plotting
import plotly.express as px
# graph
import plotly.graph_objects as go
# graph
import seaborn as sns
# t-test
from scipy import stats
# regression
from sklearn import datasets, linear_model
from sklearn.linear_model import LinearRegression
import statsmodels.api as sm
from statsmodels.formula.api import ols
# Word Cloud
from wordcloud import WordCloud
```

In [19]:
```
data=pd.read_csv('DataAnalyst.csv')
```

In [20]:
```
data.head(2)
```

Out[20]:

	Unnamed: 0	Job Title	Salary Estimate	Job Description	Rating	Company Name	Location	Headquarters	Size	Founded	Type of ownership
0	0	Data Analyst, Center on Immigration and Justic...	$37K-66K$ (Glassdoor est.)	Are you eager to roll up your sleeves and harn...	3.2	Vera Institute of Justice\n3.2	New York, NY	New York, NY	201 to 500 employees	1961	Nonprofit Organization
1	1	Quality Data Analyst	$37K-66K$ (Glassdoor est.)	Overview\n\nProvides analytical and technical ...	3.8	Visiting Nurse Service of New York\n3.8	New York, NY	New York, NY	10000+ employees	1893	Nonprofit Organization

In [21]:
```
data.describe(include='all')
```

Out[21]:

	Unnamed: 0	Job Title	Salary Estimate	Job Description	Rating	Company Name	Location	Headquarters	Size	Founded	Type of ownership	I
count	2253.0000	2253	2253	2253	2253.000000	2252	2253	2253	2253	2253.000000	2253	
unique	NaN	1272	90	2253	NaN	1513	253	483	9	NaN	15	
top	NaN	Data Analyst	$42K-$76K (Glassdoor est.)	Square builds common business tools in unconve...	NaN	Staffigo Technical Services, LLC\n5.0	New York, NY	New York, NY	51 to 200 employees	NaN	Company - Private	
freq	NaN	405	57	1	NaN	58	310	206	421	NaN	1273	
mean	1126.0000	NaN	NaN	NaN	3.160630	NaN	NaN	NaN	NaN	1398.522858	NaN	
std	650.5294	NaN	NaN	NaN	1.665228	NaN	NaN	NaN	NaN	901.929251	NaN	
min	0.0000	NaN	NaN	NaN	-1.000000	NaN	NaN	NaN	NaN	-1.000000	NaN	
25%	563.0000	NaN	NaN	NaN	3.100000	NaN	NaN	NaN	NaN	-1.000000	NaN	
50%	1126.0000	NaN	NaN	NaN	3.600000	NaN	NaN	NaN	NaN	1979.000000	NaN	
75%	1689.0000	NaN	NaN	NaN	4.000000	NaN	NaN	NaN	NaN	2002.000000	NaN	
max	2252.0000	NaN	NaN	NaN	5.000000	NaN	NaN	NaN	NaN	2019.000000	NaN	

Data Cleansing

In [22]:
```
# Check for missing values
def missing_values_table(df):
    # number of missing values
    mis_val = df.isnull().sum()
    # % of missing values
    mis_val_percent = 100 * mis_val / len(df)
    # make table # axis '0' concat along index, '1' column
    mis_val_table = pd.concat([mis_val,mis_val_percent],axis=1)
    # rename columns
    mis_val_table_ren_columns = mis_val_table.rename(
        columns = {0:'Missing Values',1:'% of Total Values'})
    # sort by column
    mis_val_table_ren_columns = mis_val_table_ren_columns[mis_val_table_ren_columns.iloc[:,1]!=0].sort_v
        '% of Total Values',ascending=False).round(1) #Review
    print("Your selected datset has "+str(df.shape[1])+" columns and "+str(len(df))+" observations.\n"
         "There are "+str(mis_val_table_ren_columns.shape[0])+" columns that have missing values.")
    # return the dataframe with missing info
    return mis_val_table_ren_columns

missing_values_table(data)
```

```
Your selected datset has 16 columns and 2253 observations.
There are 1 columns that have missing values.
```

Out[22]:

	Missing Values	% of Total Values
Company Name	1	0.0

In [23]:
```
data['Easy Apply'].value_counts()
```

Out[23]:
```
-1      2173
True      80
Name: Easy Apply, dtype: int64
```

In [24]:
```
data['Competitors'].value_counts()
```

Out[24]:
```
-1                                                    1732
Robert Half, Insight Global                             14
Adecco, Manpower                                        14
TEKsystems, Insight Global, Accenture                   10
Artech Information Systems, Mindlance, Tech Mahindra    10
                                                      ...
Attain, Deloitte, Booz Allen Hamilton                    1
TEKsystems, CGI, SDLC Partners                           1
Fiserv, First Data, Jack Henry & Associates              1
Bloomreach                                               1
Intercontinental Exchange, Euronext, Nasdaq              1
Name: Competitors, Length: 291, dtype: int64
```

we see values -1, '-1.0' , '-1'. these are garbage /null kind of values. we need to clean these up too

In [27]:
```
# Replace -1 or -1.0 or '-1' to NaN
data=data.replace(-1,np.nan)
data=data.replace(-1.0,np.nan)
data=data.replace('-1',np.nan)
```

let's now check missing values again

In [28]:
```
missing_values_table(data)
```

```
Your selected datset has 16 columns and 2253 observations.
There are 12 columns that have missing values.
```

Out[28]:

	Missing Values	% of Total Values
Easy Apply	2173	96.4
Competitors	1732	76.9
Founded	660	29.3
Industry	353	15.7
Sector	353	15.7
Rating	272	12.1
Headquarters	172	7.6
Size	163	7.2
Type of ownership	163	7.2
Revenue	163	7.2
Salary Estimate	1	0.0
Company Name	1	0.0

we see now there are more missing value columns than before. most positoons don't suport "Easy Apply" function. competitor info is missing for many.. and so on...

In [30]:
```
#Remove '\n' from Company Name.
data['Company Name'].str.split('\n', 1).str=data['Company Name'].str.split('\n', 1).str
# 1st column after split, 2nd column after split (delete when '_')
# string.split(separator, maxsplit) maxsplit default -1, which means all occurrances
```

In [36]:
```
# Split salary into two columns min salary and max salary.
data['Salary Estimate'].str.split('(', 1).str=data['Salary Estimate'].str.split('(', 1).str
```

In [44]:
```
# Split salary into two columns min salary and max salary.
data['Min_Salary'],data['Max_Salary']=data['Salary Estimate'].str.split('-').str
#data['Min_Salary']=data['Min_Salary'].str.strip(' ').str.lstrip('$').str.rstrip('K').fillna(0).astype(
#data['Max_Salary']=data['Max_Salary'].str.strip(' ').str.lstrip('$').str.rstrip('K').fillna(0).astype(
# lstrip is for removing leading characters
# rstrip is for removing rear characters
```

```
<ipython-input-44-30d2d575599d>:2: FutureWarning: Columnar iteration over characters will be deprecate
d in future releases.
  data['Min_Salary'],data['Max_Salary']=data['Salary Estimate'].str.split('-').str
```

In [46]:
```
data['Min_Salary']=data['Min_Salary'].str.strip(' ').str.lstrip('$').str.rstrip('K').fillna(0).astype('i
```

In [47]:
```
data['Max_Salary']=data['Max_Salary'].str.strip(' ').str.lstrip('$').str.rstrip('K').fillna(0).astype('i
```

In [48]:
```
data['Min_Salary']
```

Out[48]:
```
0       37
1       37
2       37
3       37
4       37
        ..
2248    78
2249    78
2250    78
2251    78
2252    78
Name: Min_Salary, Length: 2253, dtype: int64
```

In [49]:
```
data['Max_Salary']
```

Out[49]:
```
0        66
1        66
2        66
3        66
4        66
       ...
2248    104
2249    104
2250    104
2251    104
2252    104
Name: Max_Salary, Length: 2253, dtype: int64
```

In [50]:
```
#Drop the original Salary Estimate column
data.drop(['Salary Estimate'],axis=1,inplace=True)
```

In [51]:
```
# To estimate the salary with regression and other analysis, better come up with one number: Est_Salary
data['Est_Salary']=(data['Min_Salary']+data['Max_Salary'])/2
```

In [52]:
```
# Create a variable for how many years a firm has been founded
data['Years_Founded'] = 2020 - data['Founded']
```

In [53]:
```
# let's take final look at data before analysis
data.head(2)
```

Out[53]:

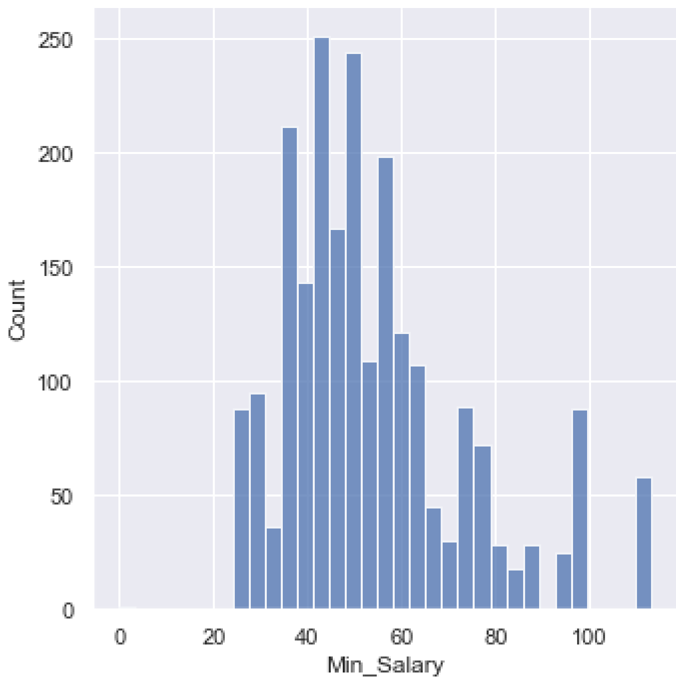
	Unnamed: 0	Job Title	Job Description	Rating	Company Name	Location	Headquarters	Size	Founded	Type of ownership	Industry	S
0	0	Data Analyst, Center on Immigration and Justic...	Are you eager to roll up your sleeves and harn...	3.2	Vera Institute of Justice	New York, NY	New York, NY	201 to 500 employees	1961.0	Nonprofit Organization	Social Assistance	
1	1	Quality Data Analyst	Overview\n\nProvides analytical and technical ...	3.8	Visiting Nurse Service of New York	New York, NY	New York, NY	10000+ employees	1893.0	Nonprofit Organization	Health Care Services & Hospitals	I

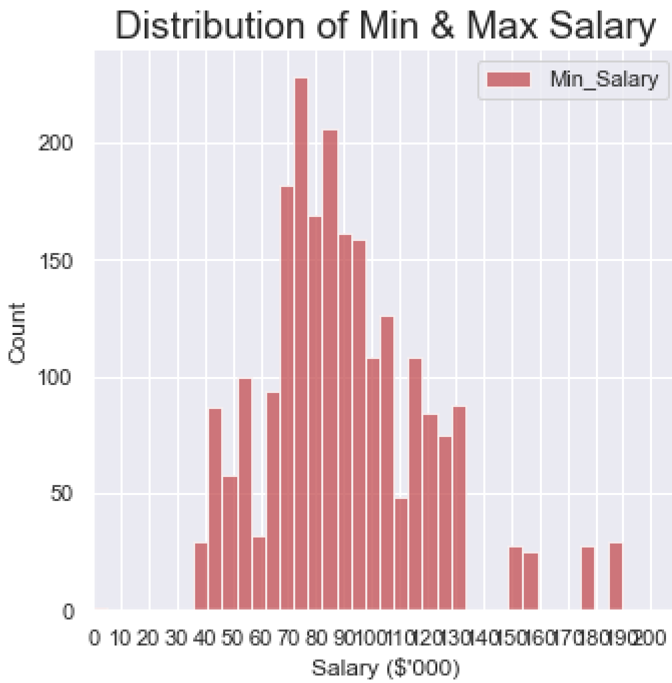
Exploratory Analysis

Salary Distribution of All Data Analysts

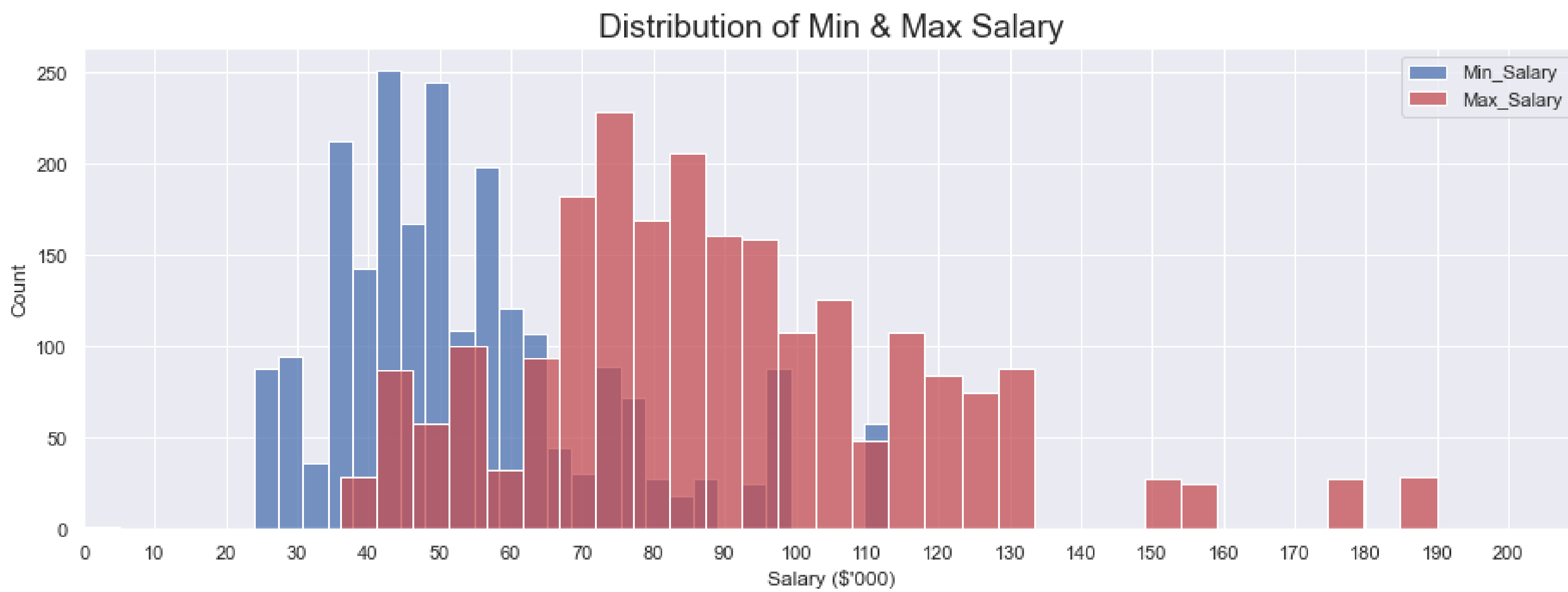
In [55]:
```
plt.figure(figsize=(13,5))
sns.set() #style==background
sns.displot(data['Min_Salary'], color="b")
sns.displot(data['Max_Salary'], color="r")

plt.xlabel("Salary ($'000)")
plt.legend({'Min_Salary':data['Min_Salary'],'Max_Salary':data['Max_Salary']})
plt.title("Distribution of Min & Max Salary",fontsize=19)
plt.xlim(0,210)
plt.xticks(np.arange(0, 210, step=10))
plt.tight_layout()
plt.show()
```

```
<Figure size 936x360 with 0 Axes>
```




Distribution of Min & Max Salary
Min_Salary
Count
0
50
100
150
200
0 10 20 30 40 50 60 70 80 90 100 110 120 130 140 150 160 170 180 190 200
Salary ($'000)

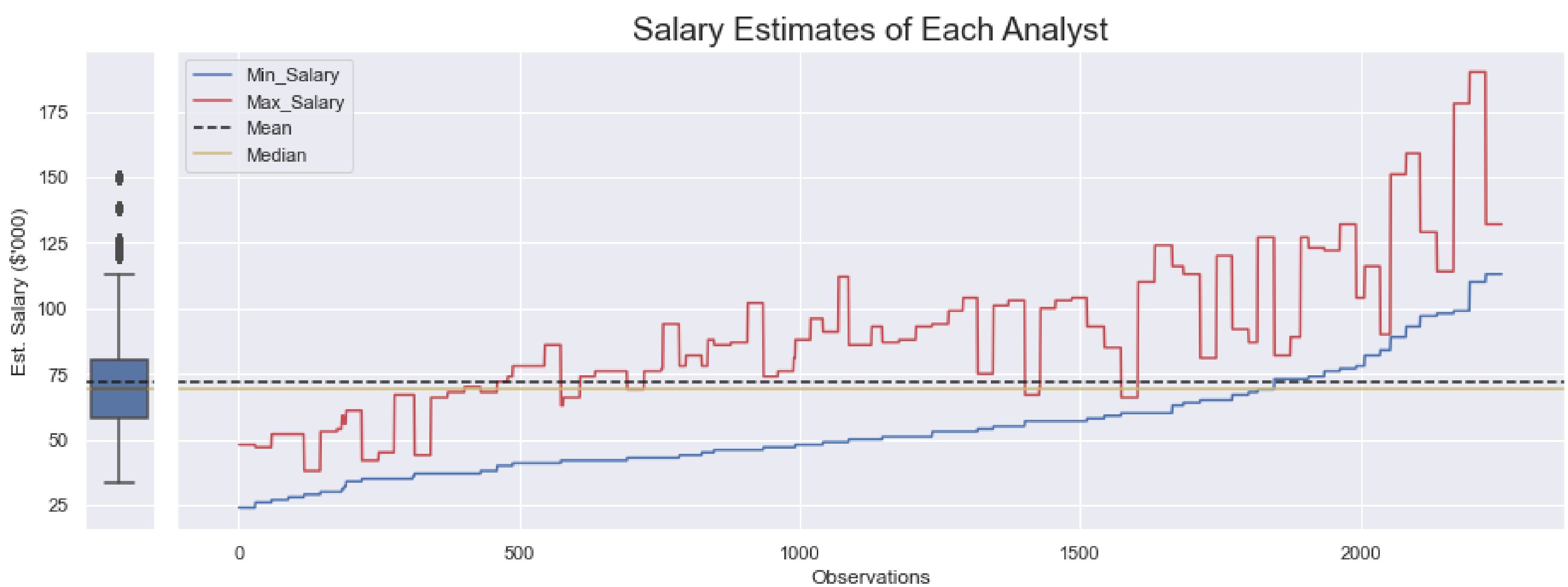
In [56]:
```
plt.figure(figsize=(13,5))
sns.set() #style==background
sns.histplot(data['Min_Salary'], color="b")
sns.histplot(data['Max_Salary'], color="r")

plt.xlabel("Salary ($'000)")
plt.legend({'Min_Salary':data['Min_Salary'],'Max_Salary':data['Max_Salary']})
plt.title("Distribution of Min & Max Salary",fontsize=19)
plt.xlim(0,210)
plt.xticks(np.arange(0, 210, step=10))
plt.tight_layout()
plt.show()
```



- Based on the modes of distribution, minimum salary is 45k and maximum is 75k
- however the spread is more incase of max_salary (it has a longer tail)

In [57]:
```
min_max_view = data.sort_values(['Min_Salary','Max_Salary'],ascending=True).reset_index(drop=True).reset
min_max_view = min_max_view.drop([0])
```

In [58]:
```
f, (ax_box, ax_line) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios": (0.05,1)},figsiz
mean=min_max_view['Est_Salary'].mean()
median=min_max_view['Est_Salary'].median()

bpv = sns.boxplot(y='Est_Salary',data=min_max_view, ax=ax_box).set(ylabel="Est. Salary ($'000)")
ax_box.axhline(mean, color='k', linestyle='--')
ax_box.axhline(median, color='y', linestyle='-')

lp1 = sns.lineplot(x='index',y='Min_Salary',data=min_max_view, color='b')
lp2 = sns.lineplot(x='index',y='Max_Salary',ax=ax_line,data=min_max_view, color='r')
ax_line.axhline(mean, color='k', linestyle='--')
ax_line.axhline(median, color='y', linestyle='-')

plt.legend({'Min_Salary':data['Min_Salary'],'Max_Salary':data['Max_Salary'],'Mean':mean,'Median':median}
plt.title("Salary Estimates of Each Analyst",fontsize=19)
plt.xlabel("Observations")
plt.tight_layout()
plt.show()
```

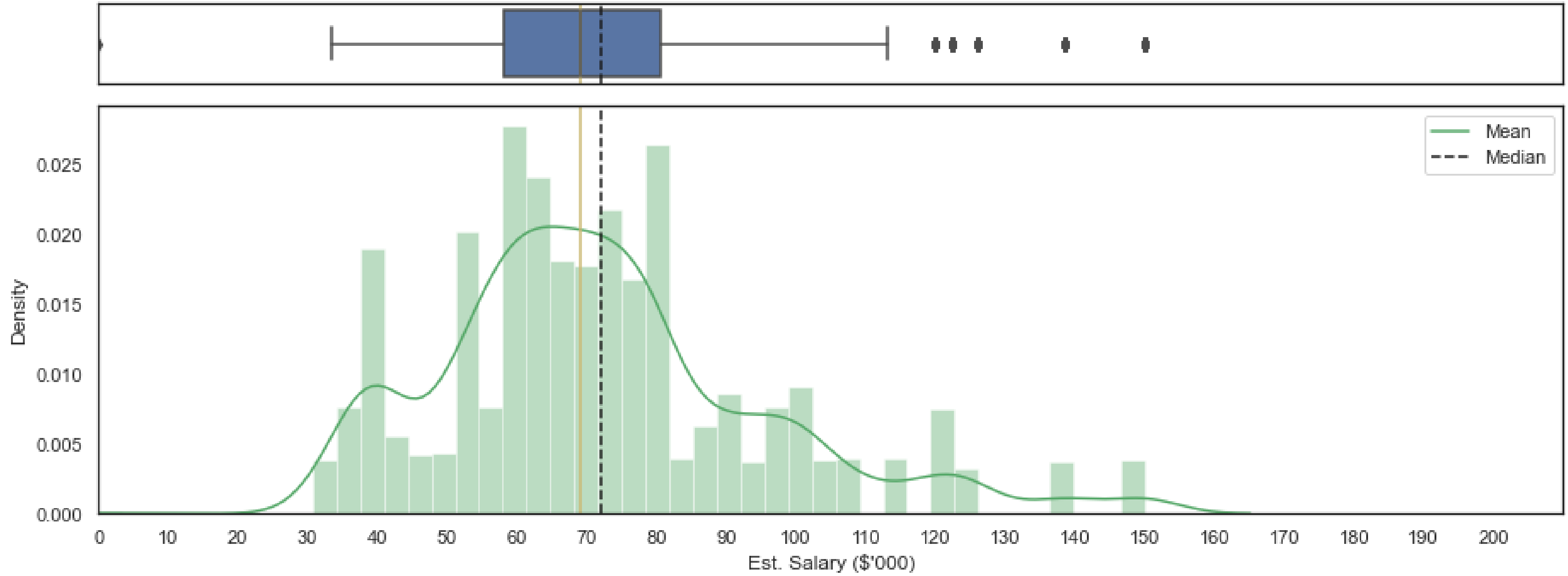


if we see anther view of dalasry distribution min, max and median

- x-axis : id (index) of all observations sorted by ascending salary min
- the min-max range estimates are more stable (flatter gradient) when min_salary ranges from 37K-50K
- salary estimates beyond 112K are outliers

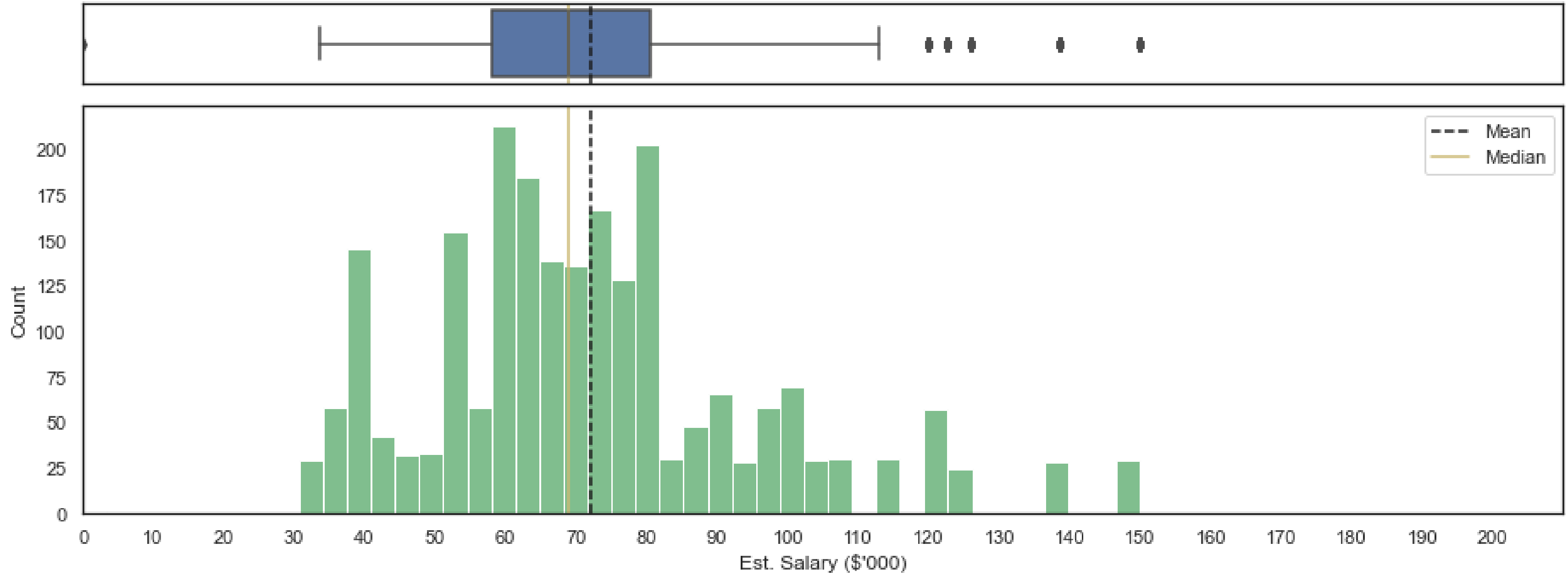
In [59]:
```
sns.set(style='white')

f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_ratios": (0.2, 1)},figsize=(13
mean=data['Est_Salary'].mean()
median=data['Est_Salary'].median()

bph = sns.boxplot(data['Est_Salary'], ax=ax_box).set(xlabel="")
ax_box.axvline(mean, color='k', linestyle='--')
ax_box.axvline(median, color='y', linestyle='-')

dp = sns.distplot(data['Est_Salary'],ax=ax_hist, color="g").set(xlabel="Est. Salary ($'000)")
ax_hist.axvline(mean, color='k', linestyle='--')
ax_hist.axvline(median, color='y', linestyle='-')

plt.legend({'Mean':mean,'Median':median})
plt.xlim(0,210)
plt.xticks(np.arange(0,210,step=10))
plt.tight_layout() #Adjust the padding between and around subplots
plt.show()
```

```
/usr/local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following va
riable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a d
eprecated function and will be removed in a future version. Please adapt your code to use either `disp
lot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for hist
ograms).
  warnings.warn(msg, FutureWarning)
```


Mean
Median
Density
0.025
0.020
0.015
0.010
0.005
0.000
0
10
20
30
40
50
60
70
80
90
100
110
120
130
140
150
160
170
180
190
200
Est. Salary ($'000)

In [60]:
```
sns.set(style='white')

f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_ratios": (0.2, 1)},figsize=(13
mean=data['Est_Salary'].mean()
median=data['Est_Salary'].median()

bph = sns.boxplot(data['Est_Salary'], ax=ax_box).set(xlabel="")
ax_box.axvline(mean, color='k', linestyle='--')
ax_box.axvline(median, color='y', linestyle='-')

dp = sns.histplot(data['Est_Salary'],ax=ax_hist, color="g").set(xlabel="Est. Salary ($'000)")
ax_hist.axvline(mean, color='k', linestyle='--')
ax_hist.axvline(median, color='y', linestyle='-')

plt.legend({'Mean':mean,'Median':median})
plt.xlim(0,210)
plt.xticks(np.arange(0,210,step=10))
plt.tight_layout() #Adjust the padding between and around subplots
plt.show()
```

```
/usr/local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following va
riable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

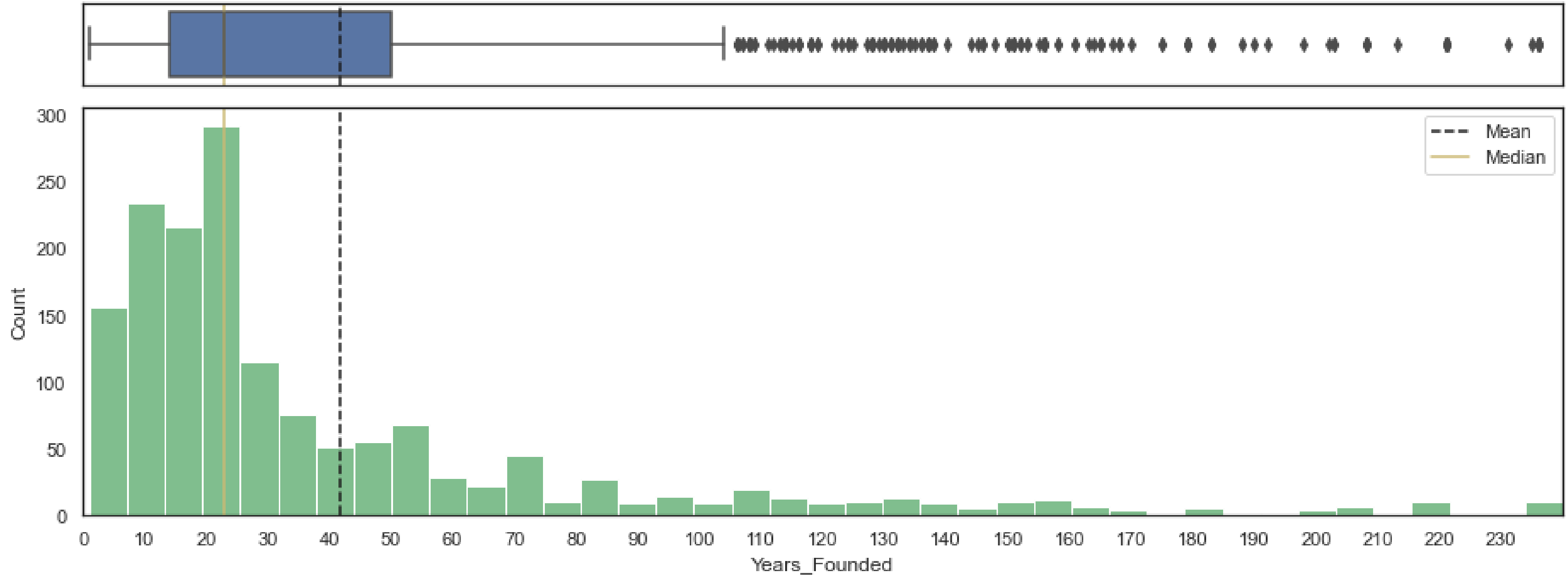


disregarding min and max, focus on Est Salary. both mean and median are ~70K

Distribution of Company Maturity /Ages

In [62]:
```
sns.set(style='white')

f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_ratios": (0.2, 1)},figsize=(13
mean=data['Years_Founded'].mean()
median=data['Years_Founded'].median()

bph = sns.boxplot(data['Years_Founded'], ax=ax_box).set(xlabel="")
ax_box.axvline(mean, color='k', linestyle='--')
ax_box.axvline(median, color='y', linestyle='-')

dp = sns.histplot(data['Years_Founded'],ax=ax_hist, color="g").set(xlabel="Years_Founded")
ax_hist.axvline(mean, color='k', linestyle='--')
ax_hist.axvline(median, color='y', linestyle='-')

plt.legend({'Mean':mean,'Median':median})
plt.xlim(0,240)
plt.xticks(np.arange(0,240,step=10))
plt.tight_layout() #Adjust the padding between and around subplots
plt.show()
```

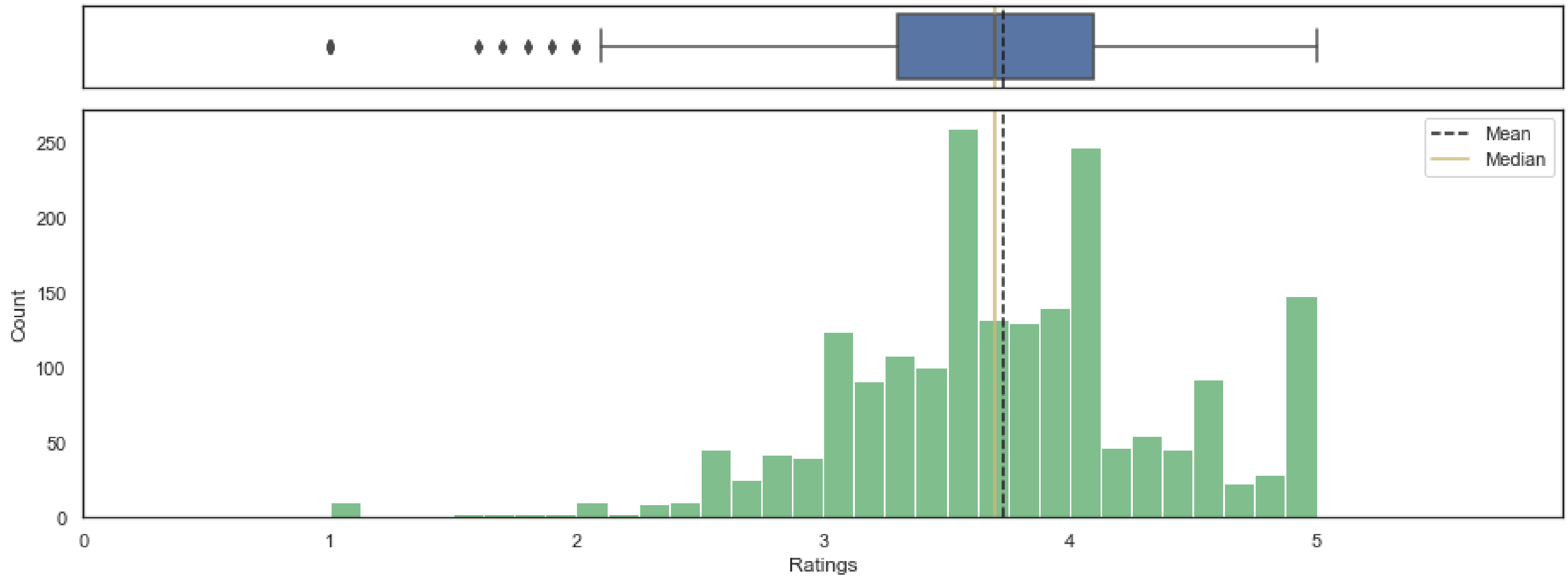
```
/usr/local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following va
riable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```



Distribution of Company Ratings

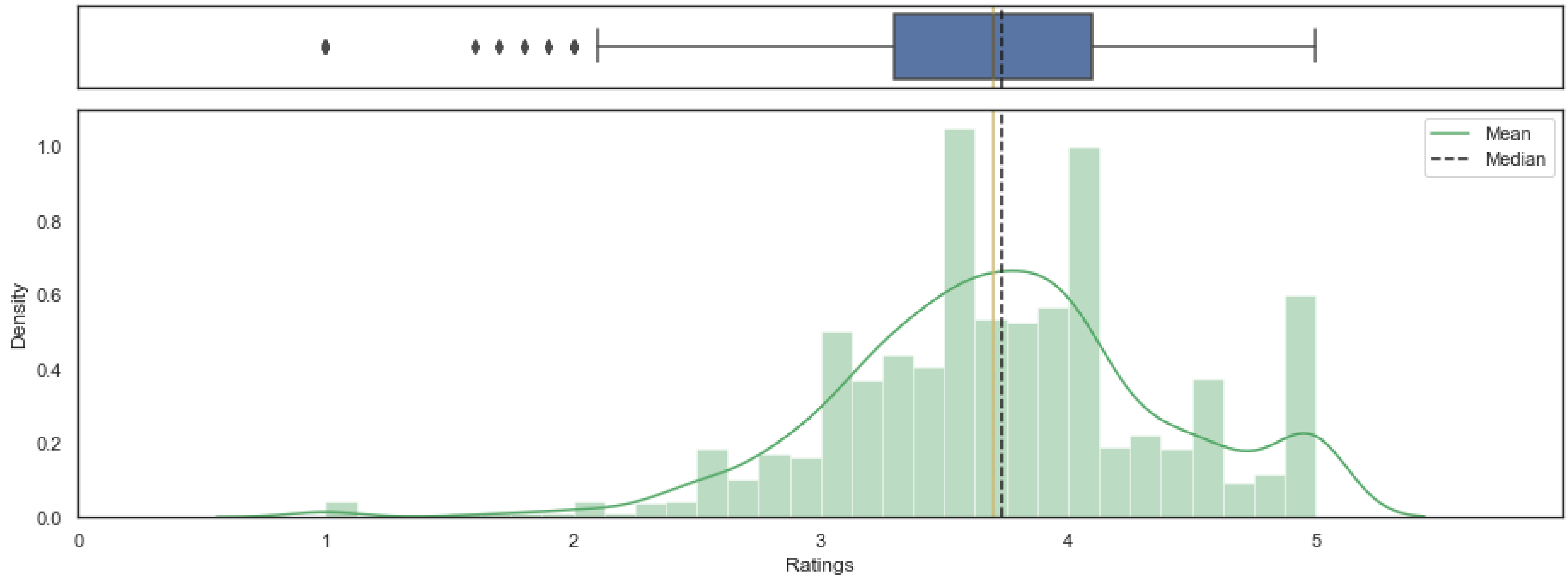
In [64]:
```
sns.set(style='white')

f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_ratios": (0.2, 1)},figsize=(13
mean=data['Rating'].mean()
median=data['Rating'].median()

bph = sns.boxplot(data['Rating'], ax=ax_box).set(xlabel="")
ax_box.axvline(mean, color='k', linestyle='--')
ax_box.axvline(median, color='y', linestyle='-')

dp = sns.histplot(data['Rating'],ax=ax_hist, color="g").set(xlabel="Ratings")
ax_hist.axvline(mean, color='k', linestyle='--')
ax_hist.axvline(median, color='y', linestyle='-')

plt.legend({'Mean':mean,'Median':median})
plt.xlim(0,6)
plt.xticks(np.arange(0,6,step=1))
plt.tight_layout() #Adjust the padding between and around subplots
plt.show()
```

```
/usr/local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following va
riable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```


Mean
Median
Count
Ratings
0
50
100
150
200
250
0
1
2
3
4
5

In [65]:
```
sns.set(style='white')

f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_ratios": (0.2, 1)},figsize=(13
mean=data['Rating'].mean()
median=data['Rating'].median()

bph = sns.boxplot(data['Rating'], ax=ax_box).set(xlabel="")
ax_box.axvline(mean, color='k', linestyle='--')
ax_box.axvline(median, color='y', linestyle='-')

dp = sns.distplot(data['Rating'],ax=ax_hist, color="g").set(xlabel="Ratings")
ax_hist.axvline(mean, color='k', linestyle='--')
ax_hist.axvline(median, color='y', linestyle='-')

plt.legend({'Mean':mean,'Median':median})
plt.xlim(0,6)
plt.xticks(np.arange(0,6,step=1))
plt.tight_layout() #Adjust the padding between and around subplots
plt.show()
```

```
/usr/local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following va
riable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a d
eprecated function and will be removed in a future version. Please adapt your code to use either `disp
lot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for hist
ograms).
  warnings.warn(msg, FutureWarning)
```



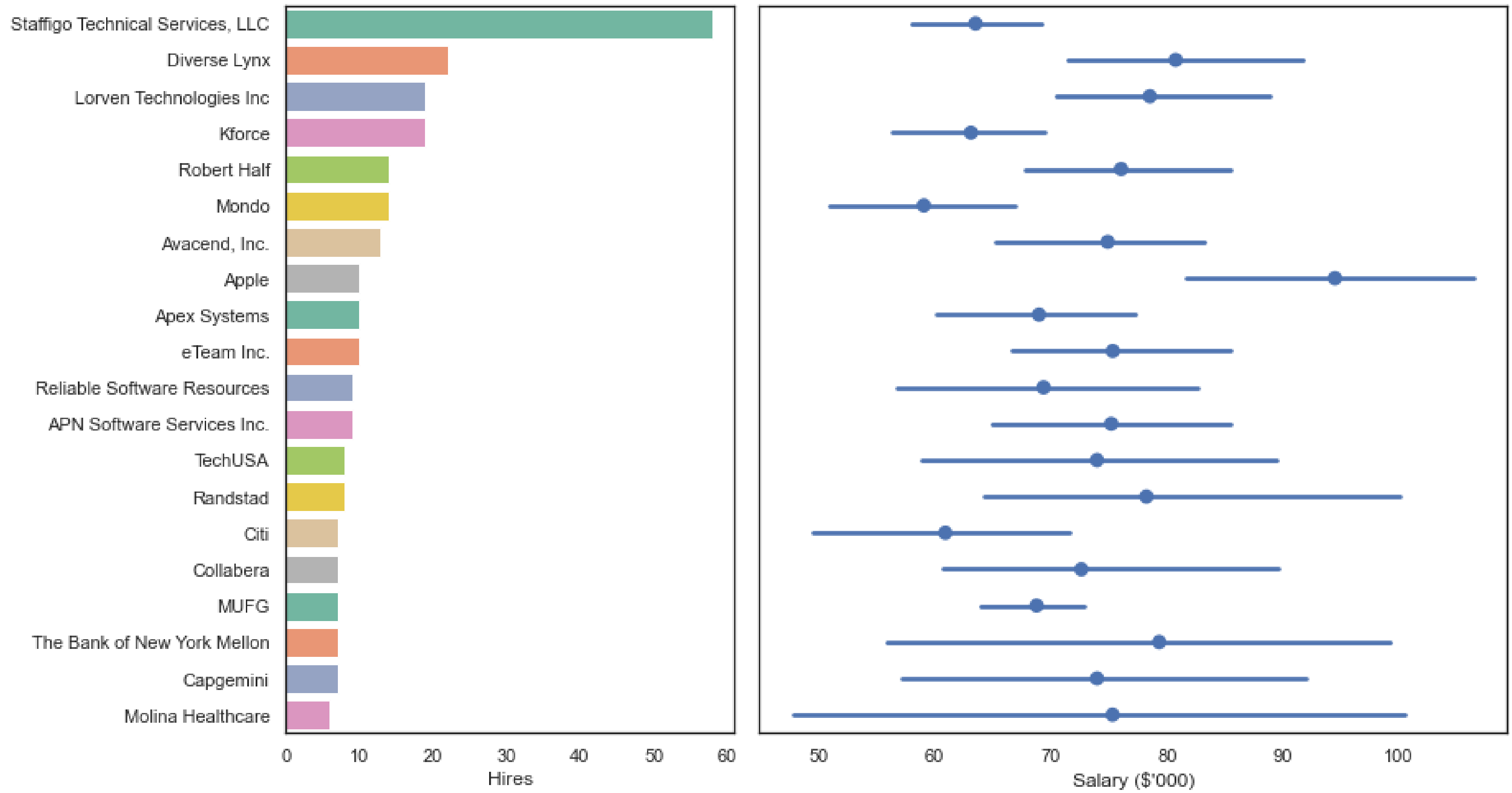
Top 20 Hiring and Salary Estimates by Firms

First step is knowing the companies that are actively hiring Data Analysts and the salry estimates being offered

In [66]:
```
# First I count the positions opened by the companies.
df_by_firm=data.groupby('Company Name')['Job Title'].count().reset_index().sort_values(
    'Job Title',ascending=False).head(20).rename(columns={'Job Title':'Hires'})
# When we reset the index, the old index is added as a column, and a new sequential index is used
```

In [67]:
```
# Merge with original data to get salary estimates.
Sal_by_firm = df_by_firm.merge(data,on='Company Name',how='left')
```

In [68]:
```
sns.set(style="white")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='Company Name',data=Sal_by_firm,ax=ax_bar, palette='Set2').set(ylabel="")
sns.pointplot(x='Est_Salary',y='Company Name',data=Sal_by_firm, join=False,ax=ax_point).set(
    ylabel="",xlabel="Salary ($'000)")

plt.tight_layout()
```



- staffigo was hiring the most number of analysts but with 4th lowest est. salary

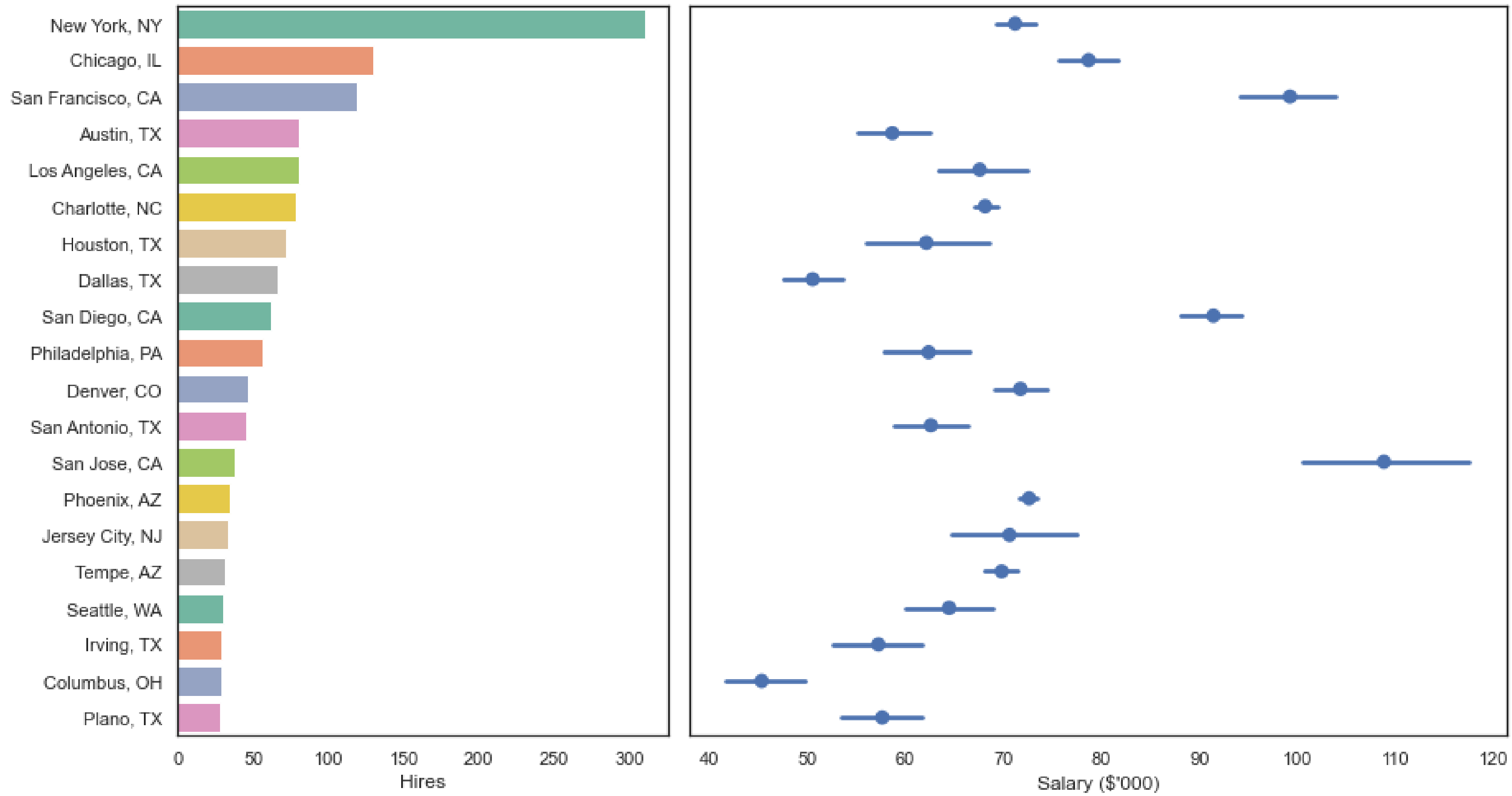
- apple has the highest est salary but the variance is large

- most sample sizes are smaller than 30, we we can assume sampling bias (and be conservative) about salary est. by firms

Top 20 Hires and Salary Estimates by Job Location Cities

In [69]:
```
df_by_city=data.groupby('Location')['Job Title'].count().reset_index().sort_values(
    'Job Title',ascending=False).head(20).rename(columns={'Job Title':'Hires'})
Sal_by_city = df_by_city.merge(data,on='Location',how='left')
```

In [70]:
```
sns.set(style="white")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='Location',data=Sal_by_city,ax=ax_bar, palette='Set2').set(ylabel="")
sns.pointplot(x='Est_Salary',y='Location',data=Sal_by_city, join=False,ax=ax_point).set(
    ylabel="",xlabel="Salary ($'000)")

plt.tight_layout()
```



- New York was hiring the most analysts with est salary at 70K
- San Jose, CA has the highest est salary and the largest variance

Hires and Salary Estimates by Job Location States

In [71]:
```
data['City'],data['State'] = data['Location'].str.split(', ',1).str
```

```
<ipython-input-71-ed103ea9ac18>:1: FutureWarning: Columnar iteration over characters will be deprecate
d in future releases.
  data['City'],data['State'] = data['Location'].str.split(', ',1).str
```

In [72]:
```
data['City']
```

Out[72]:
```
0          New York
1          New York
2          New York
3          New York
4          New York
             ...
2248         Denver
2249     Centennial
2250         Denver
2251     Centennial
2252     Broomfield
Name: City, Length: 2253, dtype: object
```

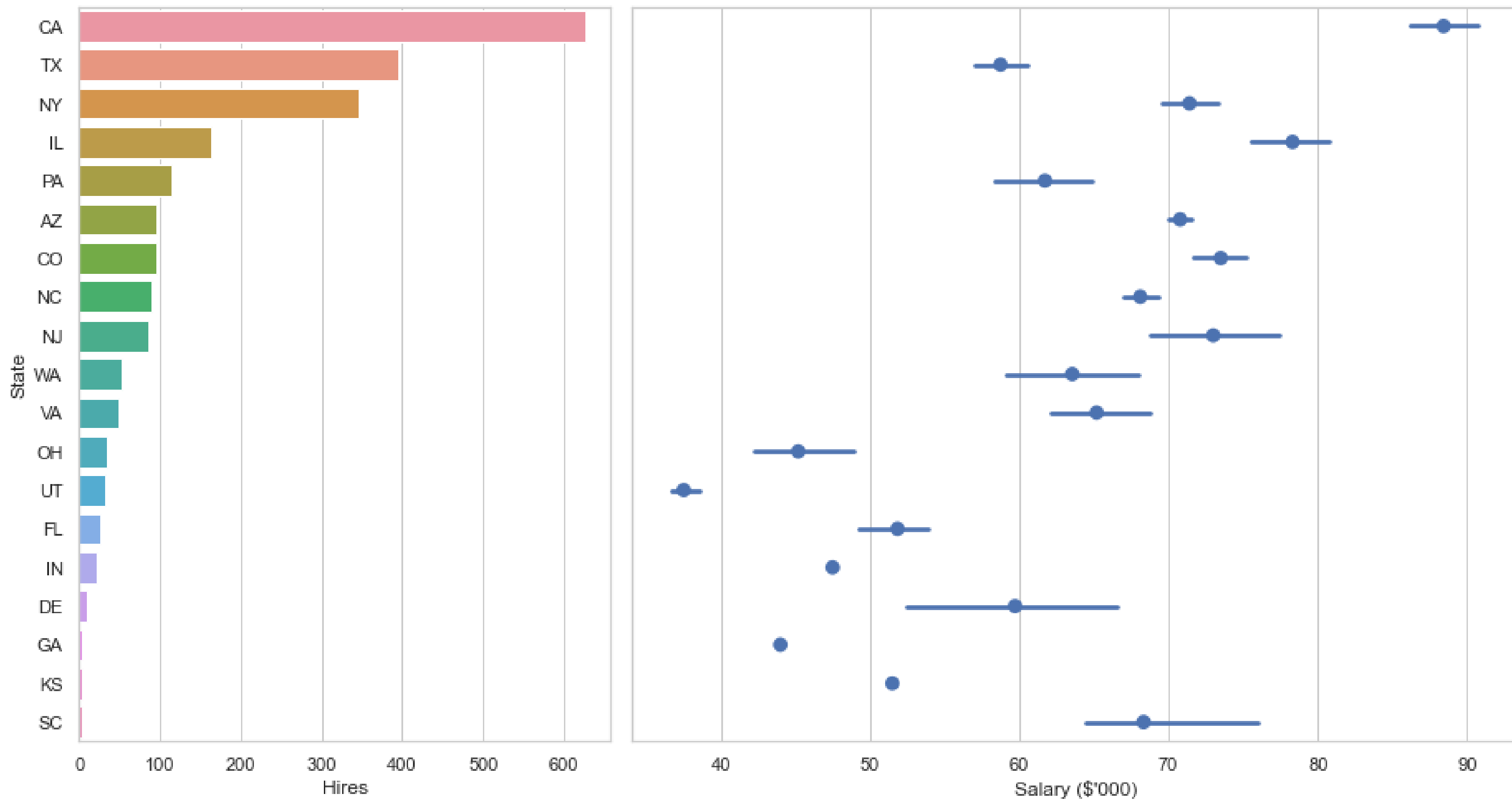
In [73]:
```
data['State']
```

Out[73]:
```
0       NY
1       NY
2       NY
3       NY
4       NY
        ..
2248    CO
2249    CO
2250    CO
2251    CO
2252    CO
Name: State, Length: 2253, dtype: object
```

In [74]:
```
data['State']=data['State'].replace('Arapahoe, CO','CO')
```

In [75]:
```
stateCount = data.groupby('State')[['Job Title']].count().reset_index().rename(columns={'Job Title':'Hi
    'Hires', ascending=False).reset_index(drop=True)
stateCount = stateCount.merge(data, on='State',how='left')
```

In [76]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='State',data=stateCount,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='State',data=stateCount, join=False,ax=ax_point).set(ylabel="",xlabel="Sa

plt.tight_layout()
```



- when viewing by states, positive correlation is more evident between demand and analysts' salaries. CA companies seem to have highest demand and are most generous with analyst hires

Top 20 Hires and Salary Estimates by Headquarters Location

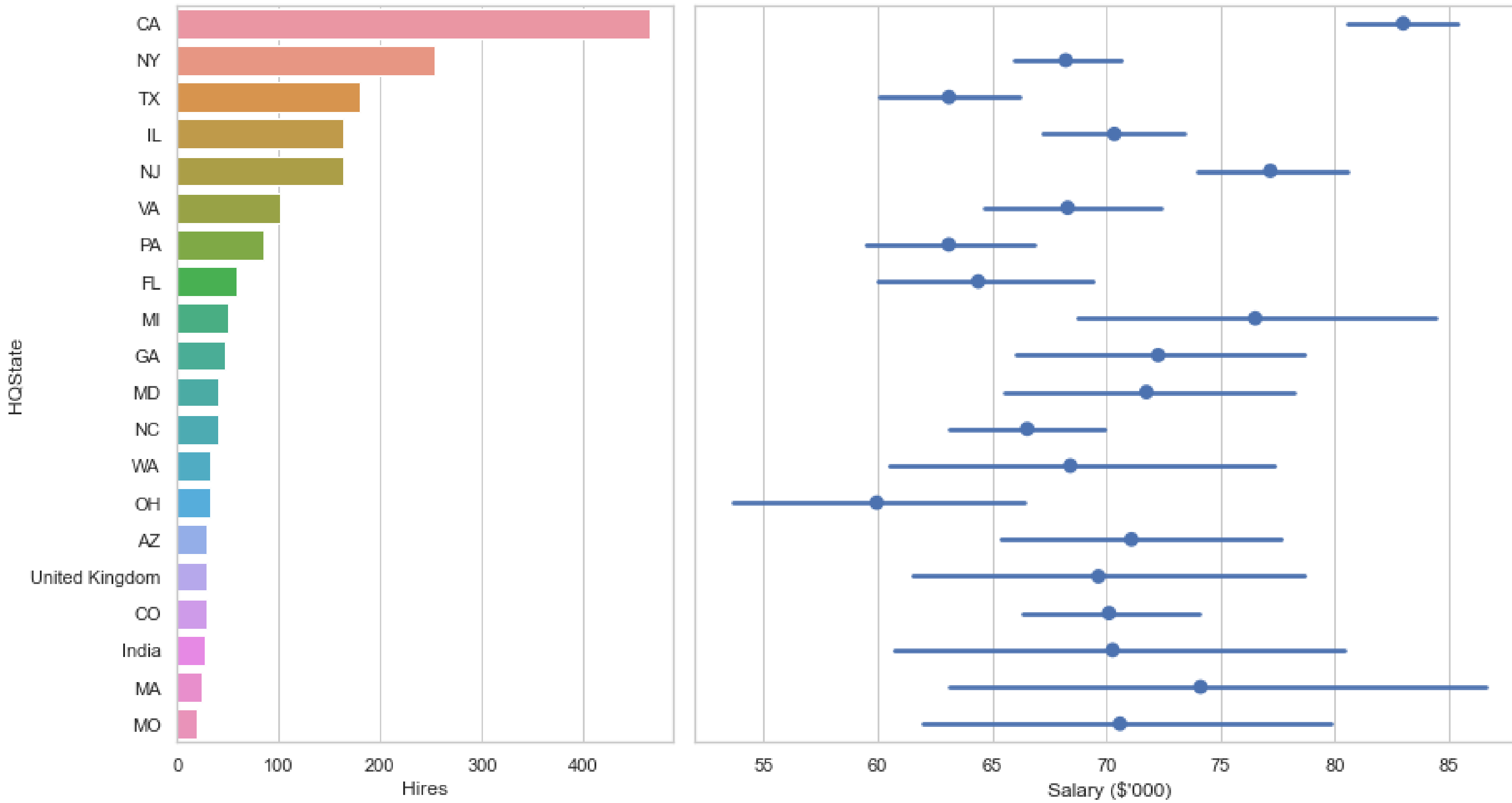
In [77]:
```
data['HQCity'],data['HQState'] = data['Headquarters'].str.split(', ',1).str
```

```
<ipython-input-77-83593a28bd6d>:1: FutureWarning: Columnar iteration over characters will be deprecate
d in future releases.
  data['HQCity'],data['HQState'] = data['Headquarters'].str.split(', ',1).str
```

In [78]:
```
data['HQState']=data['HQState'].replace('NY (US), NY','NY')
```

In [79]:
```
HQCount = data.groupby('HQState')[['Job Title']].count().reset_index().rename(columns={'Job Title':'Hire
    'Hires', ascending=False).head(20).reset_index(drop=True)
HQCount = HQCount.merge(data, on='HQState',how='left')
```

In [80]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='HQState',data=HQCount,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='HQState',data=HQCount, join=False,ax=ax_point).set(ylabel="",xlabel="Sal

plt.tight_layout()
```



- salary variance is higher in headquarter locations thyan job locations, this possibly refers to additonal factors contributing to these variations. we will dig in the regression model

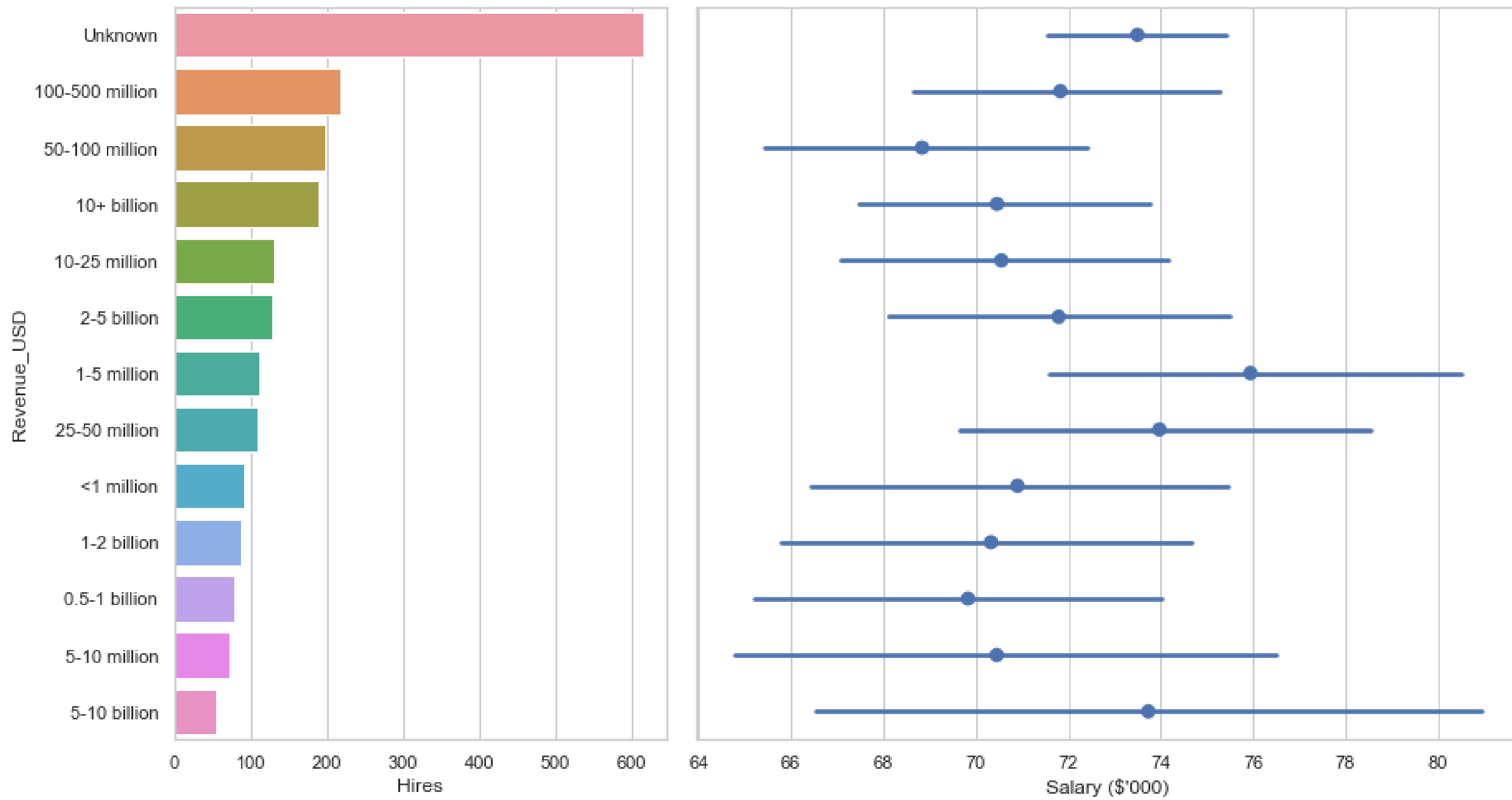
Est Salary and Hires by Revenue

In [81]:
```
RevCount = data.groupby('Revenue')[['Job Title']].count().reset_index().rename(columns={'Job Title':'Hi
    'Hires', ascending=False).reset_index(drop=True)
```

In [82]:
```
#Make the Revenue column clean
RevCount["Revenue_USD"]=['Unknown','100-500 million','50-100 million','10+ billion','10-25 million','2-5
#Merge the new Revenue back to data
RevCount2 = RevCount[['Revenue','Revenue_USD']]
RevCount = RevCount.merge(data, on='Revenue',how='left')
```

In [83]:
```
data=data.merge(RevCount2,on='Revenue',how='left')
```

In [84]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='Revenue_USD',data=RevCount,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Revenue_USD',data=RevCount, join=False,ax=ax_point).set(ylabel="",xlabel

plt.tight_layout()
```

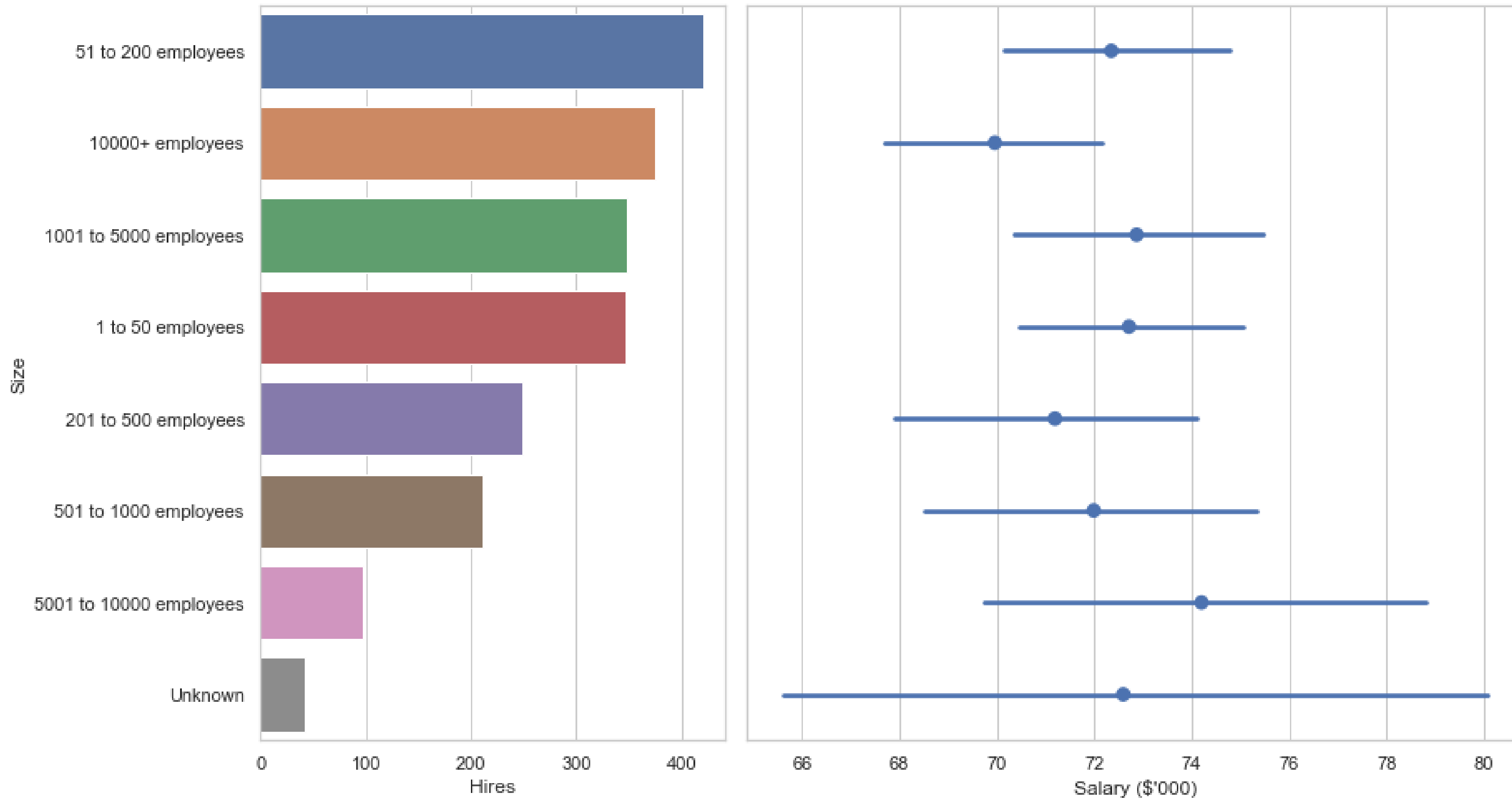


- this seems to suggest that there isnt much differentiation with analyst salary amongst big firms, in fact they do not seem to pay more for small and medium businesses for analysts

Hires and Salary Estimates by Size

In [85]:
```
SizeCount = data.groupby('Size')[['Job Title']].count().reset_index().rename(columns={'Job Title':'Hires
    'Hires', ascending=False).reset_index(drop=True)
SizeCount = SizeCount.merge(data, on='Size',how='left')
```

In [86]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='Size',data=SizeCount,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Size',data=SizeCount, join=False,ax=ax_point).set(ylabel="",xlabel="Sala

plt.tight_layout()
```

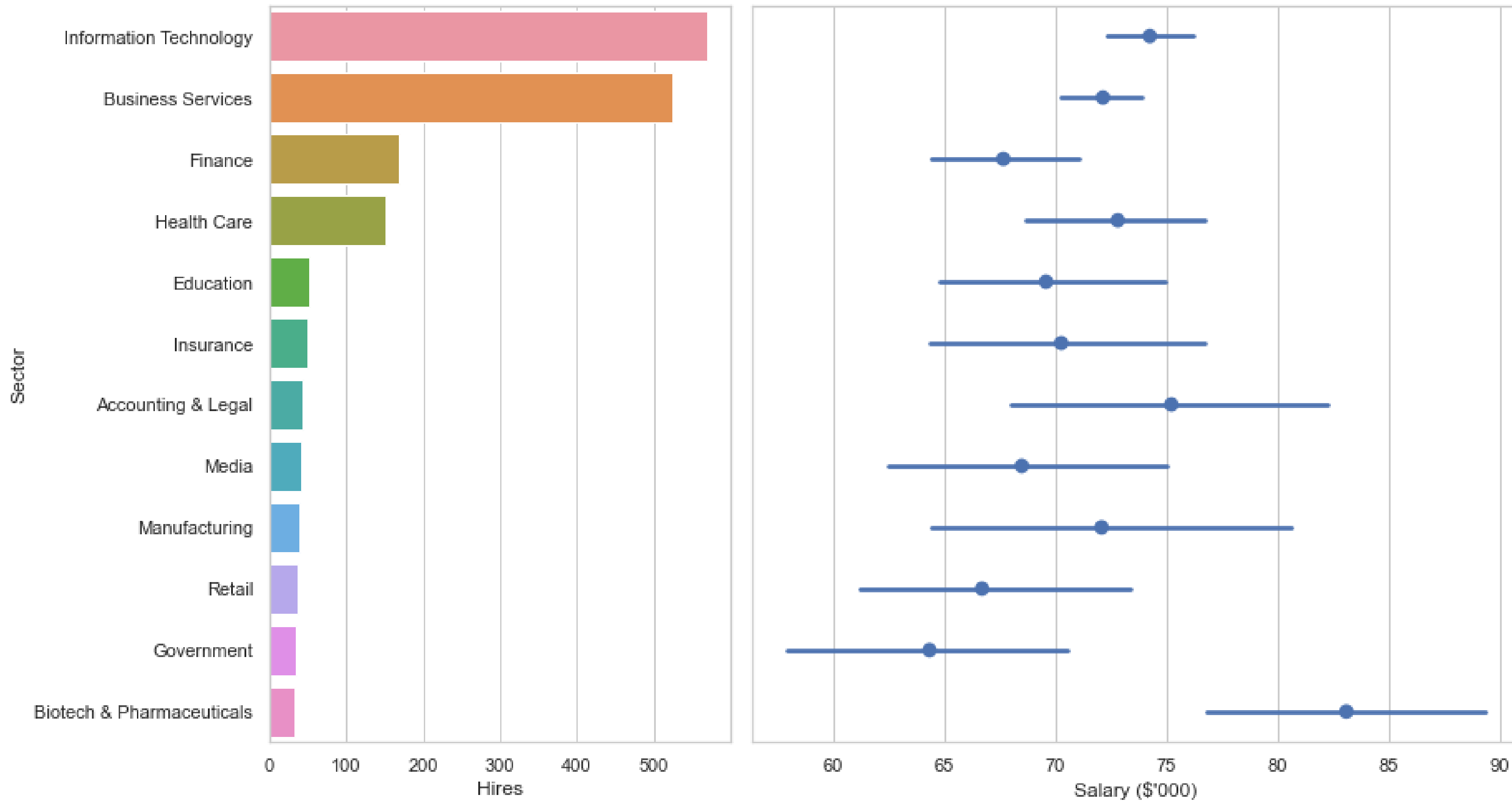


- bigger firms don't necessarily pay higher salaries

Top 12 Salary Estimates and Hiring Sectoral Trends

In [87]:
```
SecCount = data.groupby('Sector')[['Job Title']].count().reset_index().rename(columns={'Job Title':'Hire
    'Hires', ascending=False).reset_index(drop=True)
SecCount = SecCount.merge(data, on='Sector',how='left')
SecCount = SecCount[SecCount['Hires']>29]
```

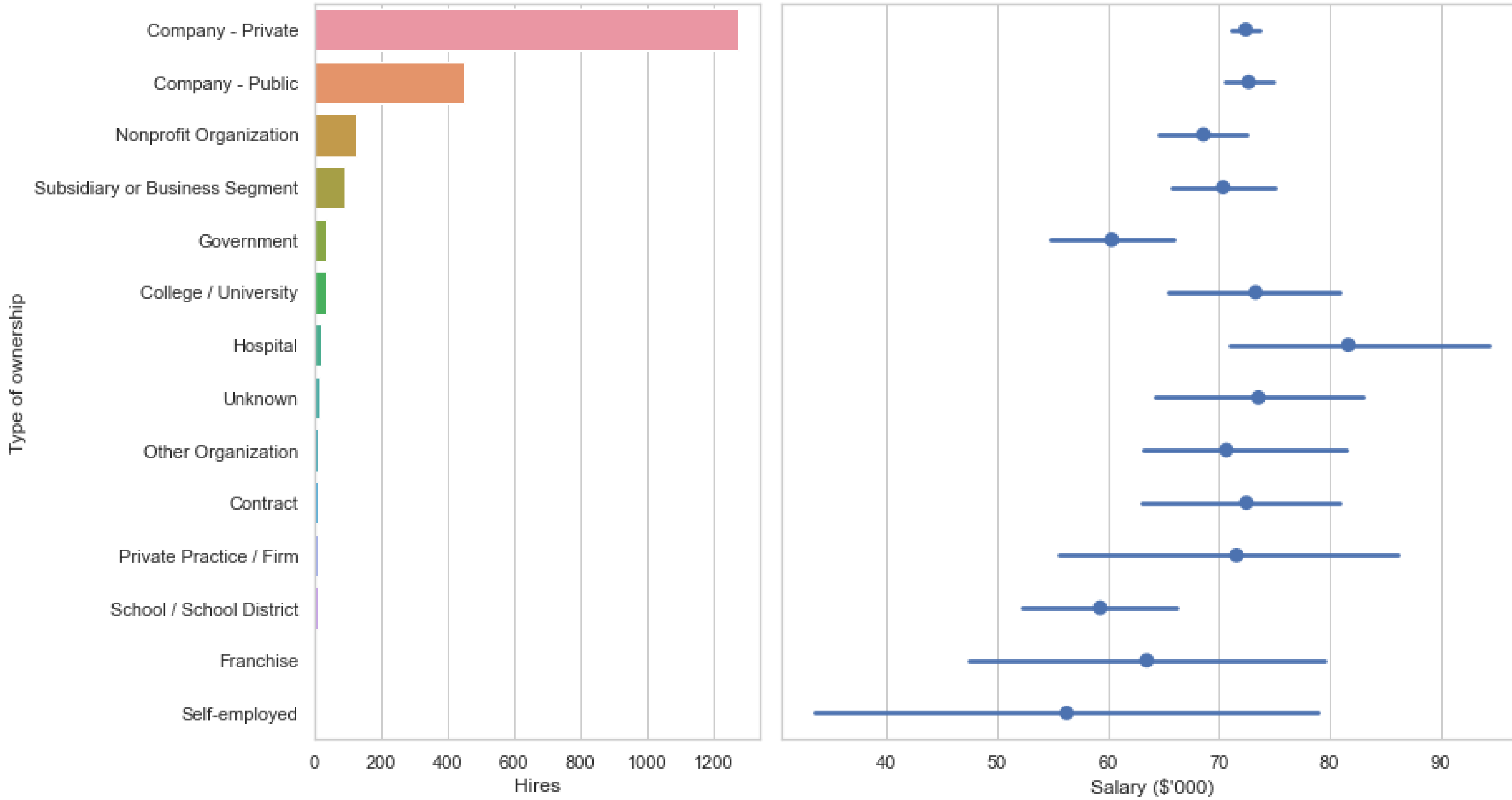
In [88]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='Sector',data=SecCount,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Sector',data=SecCount, join=False,ax=ax_point).set(ylabel="",xlabel="Sal

plt.tight_layout()
```



Hiring and Salary Estimates by Ownership Type

In [89]:
```
OwnCount = data.groupby('Type of ownership')[['Job Title']].count().reset_index().rename(columns={'Job T
    'Hires', ascending=False).reset_index(drop=True)
OwnCount = OwnCount.merge(data, on='Type of ownership',how='left')
```

In [90]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Hires',y='Type of ownership',data=OwnCount,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Type of ownership',data=OwnCount, join=False,ax=ax_point).set(ylabel="",

plt.tight_layout()
```



- demand is higher in private firms and salries are comparable with public firms

Hiring and Salary Estimates by Job Titles

need to do bit of data cleansing/rearranging to get this done

In [92]:
```
# create a new dataset from original data
text_Analysis = data[['Job Title','Job Description','Est_Salary','Max_Salary','Min_Salary','State','Easy
```

In [93]:
```
# remove special characters and unify some word use
text_Analysis['Job_title_2']= text_Analysis['Job Title'].str.upper().replace(
    [',','Â','/','\t','\n','-','AND ','&','\(','\)','WITH ','SYSTEMS','OPERATIONS','ANALYTICS','SERVICES
    ['','',' ',' ',' ',' ','',' ',' ',' ','','SYSTEM','OPERATION','ANALYTIC','SERVICE','','','ENGINEER',
# later found out replace('[^A-Za-z0-9]+', ' ',regex=True) is a simpler way to remove non-text characte
```

```
<ipython-input-93-6ced5ed5643e>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  text_Analysis['Job_title_2']= text_Analysis['Job Title'].str.upper().replace(
```

In [94]:
```
text_Analysis['Job_title_2']= text_Analysis['Job_title_2'].str.upper().replace(
    ['  ','   ','    '],
    [' ',' ',' '],regex=True)
# later found out replace('[^A-Za-z0-9]+', ' ',regex=True) is a simpler way to remove non-text characte
```

```
<ipython-input-94-59775f7874f7>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  text_Analysis['Job_title_2']= text_Analysis['Job_title_2'].str.upper().replace(
```

In [95]:

```
,'DATA ANALYST','DATA BASE','DATA QUALITY','DATA GOVERNANCE','BUSINESS ANALYST','DATA MANAGEMENT','REPOR
'DATA_MANAGEMENT','REPORTING_ANALYST','BUSINESS_DATA','SYSTEM_ANALYST','DATA_REPORTING','QUALITY_ANALYST
```

```
<ipython-input-95-af2ddcbef9f9>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  text_Analysis['Job_title_2']= text_Analysis['Job_title_2'].str.upper().replace(
```

In [96]:

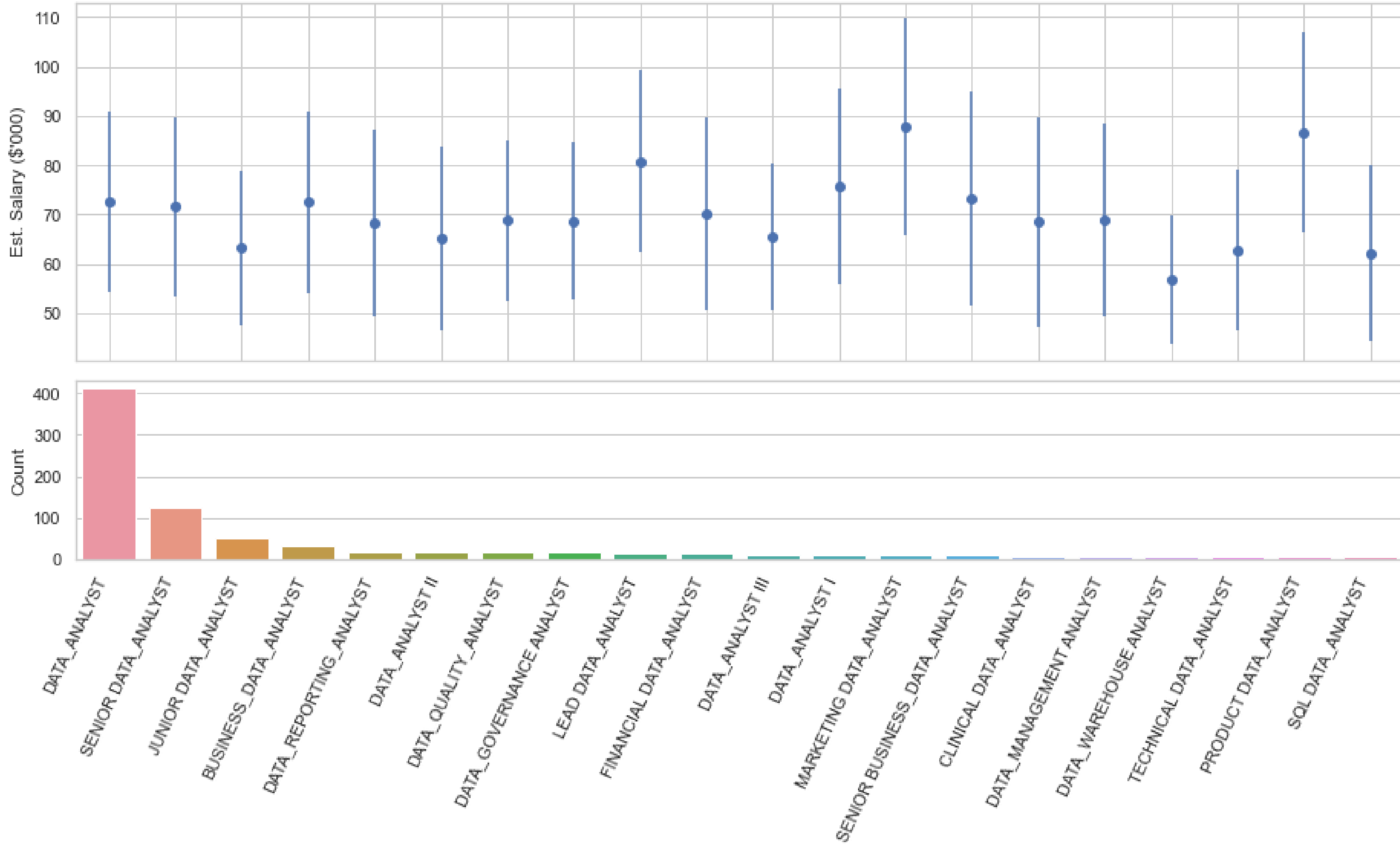
```
# unify some word use
text_Analysis['Job_title_2']= text_Analysis['Job_title_2'].str.upper().replace(
    ['DATA_ANALYST JUNIOR','DATA_ANALYST SENIOR','DATA  REPORTING_ANALYST'],
    ['JUNIOR DATA_ANALYST','SENIOR DATA_ANALYST','DATA_REPORTING_ANALYST'],regex=True)
```

```
<ipython-input-96-e978a2cab774>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  text_Analysis['Job_title_2']= text_Analysis['Job_title_2'].str.upper().replace(
```

In [97]:

```
jobCount=text_Analysis.groupby('Job_title_2')[['Job Title']].count().reset_index().rename(
    columns={'Job Title':'Count'}).sort_values('Count',ascending=False)
jobSalary = text_Analysis.groupby('Job_title_2')[['Max_Salary','Est_Salary','Min_Salary']].mean().sort_v
    ['Max_Salary','Est_Salary','Min_Salary'],ascending=False)
jobSalary['Spread']=jobSalary['Max_Salary']-jobSalary['Est_Salary']
jobSalary=jobSalary.merge(jobCount,on='Job_title_2',how='left').sort_values('Count',ascending=False).hea
```

In [98]:
```
f, axs = plt.subplots(2, sharex=True, gridspec_kw= {"height_ratios":(1,0.5)},figsize=(13,8))

ax = axs[0]
ax.errorbar(x='Job_title_2',y='Est_Salary',data=jobSalary,yerr=jobSalary['Spread'],fmt='o')
ax.set_ylabel('Est. Salary ($\'000)')

ax = axs[1]
sns.barplot(x=jobSalary['Job_title_2'],y=jobSalary['Count']).set(xlabel="")

plt.xticks(rotation=65,horizontalalignment='right')
plt.tight_layout()
```



(most sample size is below 30) this doesn't seem any better conclusive -- since we have standarized role titles

Regression model maybe a better approach, some titles/role desc maybe correlated with salary

Regression Analysis

Correlation: Job Title Keywords vs Salary

In [99]:
```
# get top keywords
s = text_Analysis['Job_title_2'].str.split(expand=True).stack().value_counts().reset_index().rename(
    columns={'index':'KW',0:'Count'})
S = s[s['Count']>29]
S
```

Out[99]:

	KW	Count
0	DATA_ANALYST	1596
1	DATA	444
2	ANALYST	422
3	SENIOR	415
4	ANALYTIC	81
5	BUSINESS_ANALYST	75
6	JUNIOR	71
7	BUSINESS_DATA_ANALYST	71
8	FINANCIAL	61
9	LEAD	60
10	HEALTHCARE	55
11	BI	49
12	II	47
13	DATA_MANAGEMENT	45
14	OPERATION	45
15	DATA_REPORTING_ANALYST	44
16	DATA_GOVERNANCE	43
17	SQL	42
18	III	39
19	ENGINEER	39
20	SECURITY	39

	KW	Count
21	PRODUCT	37
22	MARKETING	35
23	DATA_QUALITY_ANALYST	33
24	DATA_WAREHOUSE	32
25	SYSTEM_ANALYST	31
26	TECHNICAL	30

In [100]:

```
# write get_keyword method
def get_keyword(x):
   x_ = x.split(" ")
   keywords = []
   try:
      for word in x_:
         if word in np.asarray(S['KW']):
            keywords.append(word)
   except:
      return -1

   return keywords
```

In [101]:

```
# get keywords from each row
text_Analysis['KW'] = text_Analysis['Job_title_2'].apply(lambda x: get_keyword(x))
```

```
<ipython-input-101-3c511b91d267>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  text_Analysis['KW'] = text_Analysis['Job_title_2'].apply(lambda x: get_keyword(x))
```

In [102]:

```
# create dummy columns by keywords
kwdummy = pd.get_dummies(text_Analysis['KW'].apply(pd.Series).stack()).sum(level=0).replace(2,1)
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True).replace(np.nan,0)
```

In [103]:
```
# drop 2149 because unpaid analyst is not usual
text_Analysis = text_Analysis.drop([2149])
```

In [104]:
```
# run t-test for top keywords to see their correlation with salaries
text_columns = list(text_Analysis.columns)
ttests=[]
for word in text_columns:
    if word in set(S['KW']):
        ttest = stats.ttest_ind(text_Analysis[text_Analysis[word]==1]['Est_Salary'],
                                             text_Analysis[text_Analysis[word]==0]['Est_Salary'])
        ttests.append([word,ttest])

ttests = pd.DataFrame(ttests,columns=['KW','R'])
ttests['R']=ttests['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],['','',''],re
ttests['Statistic'],ttests['P-value']=ttests['R'].str.split(', ',1).str
ttests=ttests.drop(['R'],axis=1).sort_values('P-value',ascending=True)
ttests
```

```
<ipython-input-104-f8f7376ad899>:12: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests['Statistic'],ttests['P-value']=ttests['R'].str.split(', ',1).str
```

Out[104]:

	KW	Statistic	P-value
17	JUNIOR	-3.16113963777975	0.0015924799011453933
23	SENIOR	2.566621092906869	0.010333747177703521
15	II	-2.1641385068743015	0.03055880685141866
3	BUSINESS_ANALYST	-2.1143597122716233	0.03459447375320005
7	DATA_GOVERNANCE	-1.8975635628304668	0.05788172852566256
19	MARKETING	1.8774876846011315	0.06058078348826275
13	FINANCIAL	1.835680174229379	0.0665371085981364
1	ANALYTIC	1.245309555431649	0.21314788797933895
12	ENGINEER	1.157710993595735	0.24710509321020943
11	DATA_WAREHOUSE	1.0833330747872112	0.27877689285686663
24	SQL	-1.0483759488135824	0.2945782288955317
20	OPERATION	1.0351679126277473	0.30070194151819885
4	BUSINESS_DATA_ANALYST	1.015768026552328	0.309849271946996

	KW	Statistic	P-value
9	DATA_QUALITY_ANALYST	-0.9949822464900087	0.31985207929367593
5	DATA	-0.9332817097097893	0.35077489814890705
18	LEAD	0.8492663921783803	0.3958235875094457
6	DATA_ANALYST	0.7817472687608902	0.43444551526084385
21	PRODUCT	0.7615516876396424	0.4464075726642809
26	TECHNICAL	0.6299365175356518	0.5288001969160389
2	BI	-0.5900233001467271	0.5552343816068435
25	SYSTEM_ANALYST	0.5230526446856699	0.6009892132133554
22	SECURITY	0.5116348202290237	0.6089569076363668
14	HEALTHCARE	-0.4626090256907169	0.6436894511293966
0	ANALYST	-0.3629695713272434	0.7166617700129941
16	III	-0.24348098561520456	0.8076550488640784
8	DATA_MANAGEMENT	-0.07057099376465448	0.9437454791887261
10	DATA_REPORTING_ANALYST	-0.038420912849882964	0.9693555018008357

In [105]:

```
# Selecting keywords with p-value <0.1 into multiple regression model.
ttest_pass = list(ttests[ttests['P-value'].astype(float)<0.1]['KW'])
print(*ttest_pass,sep=' + ')
```

```
JUNIOR + SENIOR + II + BUSINESS_ANALYST + DATA_GOVERNANCE + MARKETING + FINANCIAL
```

In [106]:
```
# Run initial regression model.
titleMod = ols("Est_Salary ~ JUNIOR + SENIOR + II + BUSINESS_ANALYST + DATA_GOVERNANCE + MARKETING + FIN
               data=text_Analysis).fit()
print(titleMod.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.015
Model:                            OLS   Adj. R-squared:                  0.012
Method:                 Least Squares   F-statistic:                     4.814
Date:                Thu, 19 Nov 2020   Prob (F-statistic):           2.15e-05
Time:                        20:27:16   Log-Likelihood:                -10280.
No. Observations:                2248   AIC:                         2.058e+04
Df Residuals:                    2240   BIC:                         2.062e+04
Df Model:                           7
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept           72.0942      0.588    122.666      0.000      70.942      73.247
JUNIOR              -8.7228      2.867     -3.043      0.002     -14.344      -3.101
SENIOR               2.8186      1.283      2.196      0.028       0.302       5.336
II                  -7.2627      3.467     -2.095      0.036     -14.062      -0.463
BUSINESS_ANALYST    -5.5569      2.797     -1.986      0.047     -11.043      -0.071
DATA_GOVERNANCE     -5.9782      3.643     -1.641      0.101     -13.122       1.166
MARKETING            7.0020      4.061      1.724      0.085      -0.962      14.965
FINANCIAL            5.0490      3.051      1.655      0.098      -0.935      11.033
==============================================================================
Omnibus:                      277.301   Durbin-Watson:                   0.080
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              405.048
Skew:                           0.907   Prob(JB):                     1.11e-88
Kurtosis:                       4.016   Cond. No.                         8.40
==============================================================================

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

In [107]:
```
# Remove variables with p-value >0.05 one by one until all <0.05
titleMod_final = ols("Est_Salary ~ JUNIOR + SENIOR + II + BUSINESS_ANALYST",
                     data=text_Analysis).fit()
print(titleMod_final.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.011
Model:                            OLS   Adj. R-squared:                  0.009
Method:                 Least Squares   F-statistic:                     6.286
Date:                Thu, 19 Nov 2020   Prob (F-statistic):           5.00e-05
Time:                        20:27:36   Log-Likelihood:                -10284.
No. Observations:                2248   AIC:                         2.058e+04
Df Residuals:                    2243   BIC:                         2.061e+04
Df Model:                           4
Covariance Type:            nonrobust
====================================================================================
                       coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------
Intercept           72.2511      0.574    125.882      0.000      71.126      73.377
JUNIOR              -8.8796      2.867     -3.097      0.002     -14.502      -3.257
SENIOR               2.8541      1.285      2.221      0.026       0.334       5.374
II                  -7.5333      3.470     -2.171      0.030     -14.338      -0.729
BUSINESS_ANALYST    -6.2954      2.780     -2.265      0.024     -11.747      -0.844
==============================================================================
Omnibus:                      280.615   Durbin-Watson:                   0.073
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              411.585
Skew:                           0.914   Prob(JB):                     4.22e-90
Kurtosis:                       4.026   Cond. No.                         7.16
==============================================================================

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

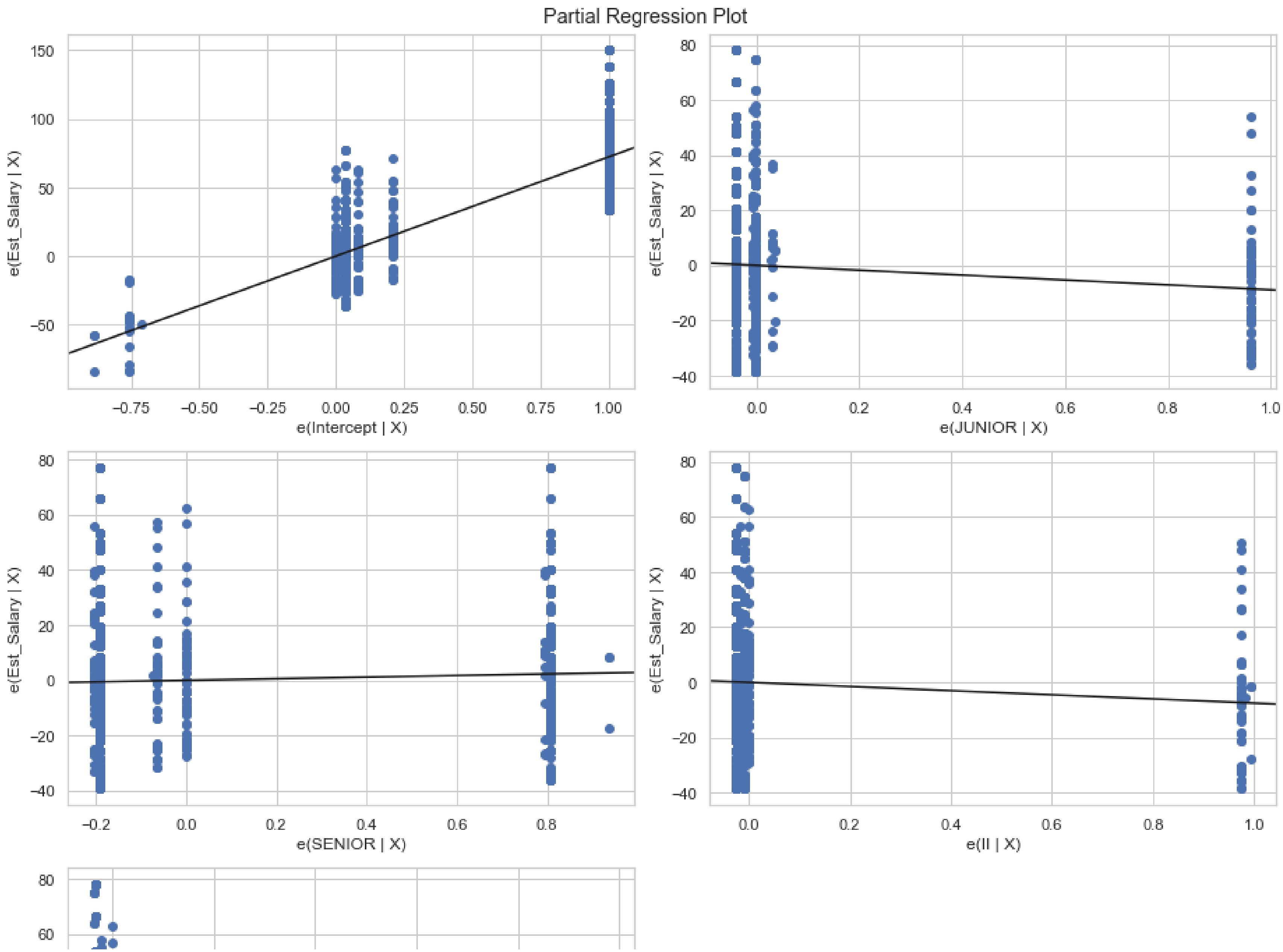
- seniorities seem to have more relevance than fucntional keywords like marketing, finance

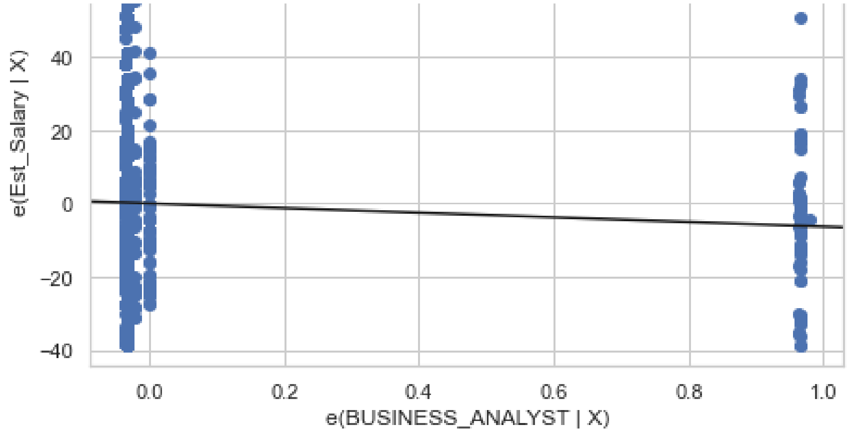
- "business analyst" paid less than "data analyst" or other forms or "analyst". Only thing to note is such jobs are less based in CA (and probably that is reason)

- cannot exactly explain variation in salaries or this model explains less than 1% salary variations

I didnt find anything new when checking for interaction terms between business_analyst and seniorities

In [108]:
```
# Plot with scatterplots
fig = plt.figure(figsize=(13, 13))
fig = sm.graphics.plot_partregress_grid(titleMod_final,fig=fig)
fig.tight_layout(pad=1.0)
# Sorry somebody tell me how to remove that "Partial Regression Plot"
```





Correlation: Job Description vs Salary

In [109]:
```
text_Analysis['Job_Desc2'] = text_Analysis['Job Description'].replace('[^A-Za-z0-9]+', ' ',regex=True)
```

In [110]:
```

ORK','NATURAL LANGUAGE PROCESSING','DECISION TREE','CLUSTERING','PL SQL'],
LGORITHM','DEEP_LEARNING','NEURAL_NETWORK','NATURAL_LANGUAGE_PROCESSING','DECISION_TREE','CLUSTER','PLSQL
```

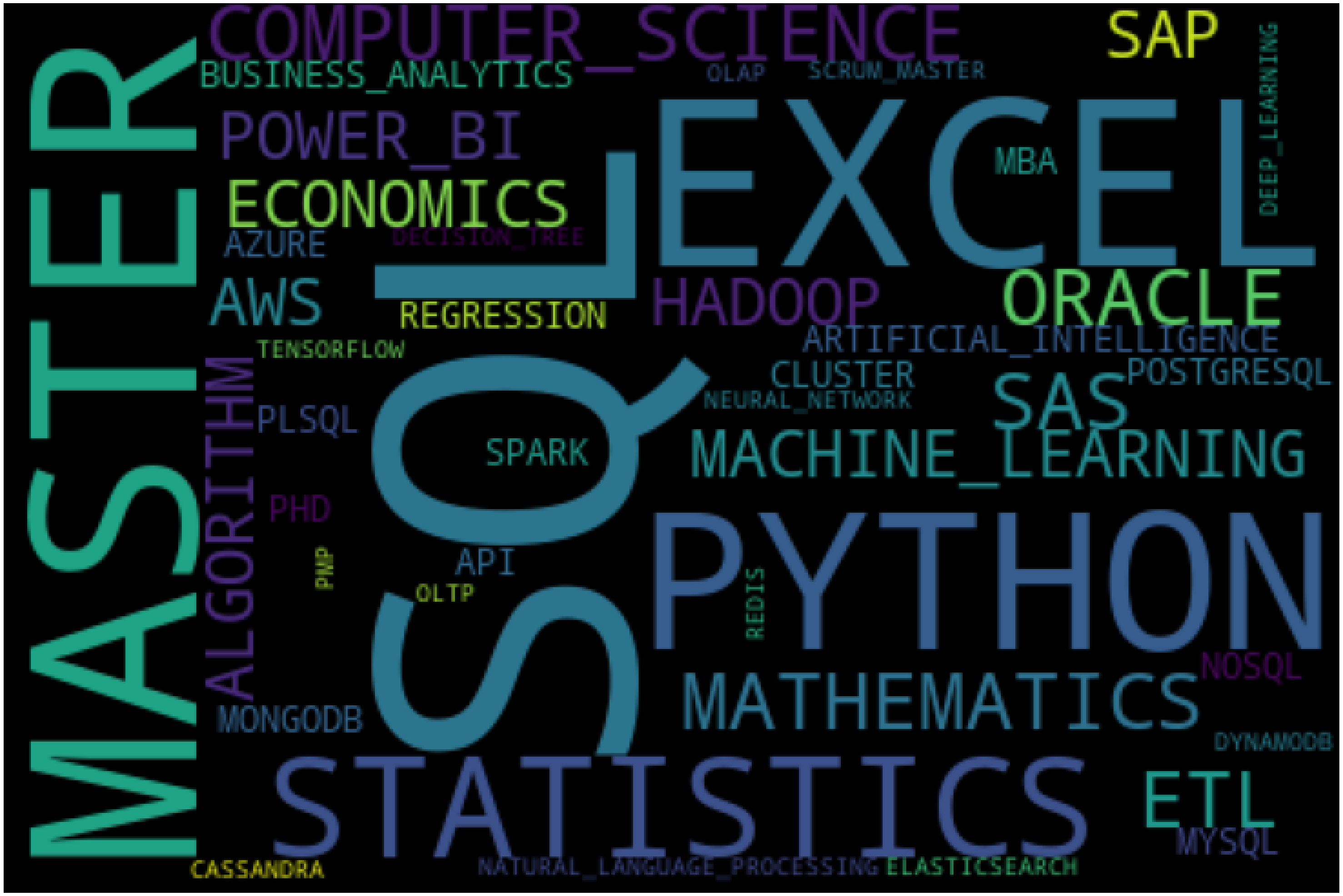
In [111]:
```

PLSQL','MONGODB','POSTGRESQL','ELASTICSEARCH','REDIS','MYSQL','FIREBASE','SQLITE','CASSANDRA','DYNAMODB'
```

In [112]:
```
# Count the JD keywords.
S2 = text_Analysis['Job_Desc2'].str.split(expand=True).stack().value_counts().reset_index().rename(
    columns={'index':'KW',0:'Count'})
S2 = S2[S2['KW'].isin(buzzwords)].reset_index(drop=True)
# .sort_values('Count',ascending=False)
S2_TOP = S2[S2['Count']>29]
S2_TOP_JD = S2_TOP
S2_TOP_JD['KW'] = S2_TOP_JD['KW'] +'_JD'
```

```
<ipython-input-112-d2f3213f649d>:8: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  S2_TOP_JD['KW'] = S2_TOP_JD['KW'] +'_JD'
```

In [113]:
```
wordCloud = WordCloud(width=450,height= 300).generate(' '.join(S2['KW']))
plt.figure(figsize=(19,9))
plt.axis('off')
plt.title("Keywords in Data Analyst Job Descriptions",fontsize=20)
plt.imshow(wordCloud)
plt.show()
```

Keywords in Data Analyst Job Descriptions



In [114]:
```
# write get_keyword method
def get_keyword(x):
    x_ = x.split(" ")
    keywords = []
    try:
        for word in x_:
            if word + '_JD' in np.asarray(S2_TOP_JD['KW']):
                keywords.append(word + '_JD')
    except:
        return -1

    return keywords
```

In [115]:
```
# get keywords from each row
text_Analysis['JDKW'] = text_Analysis['Job_Desc2'].apply(lambda x: get_keyword(x))
```

In [116]:
```
# create dummy columns by keywords
kwdummy = pd.get_dummies(text_Analysis['JDKW'].apply(pd.Series).stack()).sum(level=0)
# Since a JD sometimes repeat a keyword, the value may >1
# But what we want to know is whether the appearance of the keyword impact the salary, not frequency
# So values >1 have to be replaced by 1, but there must be a better way than coding like this ↓
kwdummy = kwdummy.replace([1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18],
                          [1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1,1])
```

In [117]:
```
# merge back the dummy columns to the main dataset
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True,how='left').replace(np.nan,
```

In [118]:
```
# let's see if number of buzzwords contained or how wordy the JD is would have impact.
text_Analysis['JDKWlen']=text_Analysis['JDKW'].str.len()
text_Analysis['JDlen']=text_Analysis['Job Description'].str.len()
```

In [119]:
```
# run t-test for top keywords to see their correlation with salaries
text_columns = list(text_Analysis.columns)
ttests_JD=[]
for word in text_columns:
    if word in set(S2_TOP_JD['KW']):
        ttest2 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                                 text_Analysis[text_Analysis[word]==0]['Est_Salary'])
        ttests_JD.append([word,ttest2])

ttests_JD = pd.DataFrame(ttests_JD,columns=['KW','R'])
ttests_JD['R']=ttests_JD['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],['','',
ttests_JD['Statistic'],ttests_JD['P-value']=ttests_JD['R'].str.split(', ',1).str
ttests_JD=ttests_JD.drop(['R'],axis=1).sort_values('P-value',ascending=True)
ttests_JD
```

```
<ipython-input-119-c3367abeb7fb>:12: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_JD['Statistic'],ttests_JD['P-value']=ttests_JD['R'].str.split(', ',1).str
```

Out[119]:

	KW	Statistic	P-value
22	PYTHON_JD	3.1454855202979366	0.0016798148989789698
16	MYSQL_JD	3.073582279739166	0.0021404726691396977
18	PHD_JD	2.8709801722675983	0.004130334861569249
26	SAS_JD	-2.5328088192719864	0.01138282238652457
17	ORACLE_JD	2.1291517828797053	0.033350204531353816
13	MASTER_JD	-2.0530455554133247	0.040183761597212785
9	ETL_JD	-1.9599639883423432	0.05012348235884792
14	MATHEMATICS_JD	-1.5597368064751596	0.1189629754350605
10	EXCEL_JD	-1.521605446498184	0.12824873859143365
19	PLSQL_JD	1.3807487956234472	0.16749359079126214
0	ALGORITHM_JD	1.3326785131639587	0.18277250666211392
27	SPARK_JD	1.2968609421931672	0.19481224787698476
4	AZURE_JD	-1.2830068757025375	0.19962204281024332

	KW	Statistic	P-value
24	R_JD	1.2814987470266699	0.20015082203688633
21	POWER_BI_JD	-1.2476710486543665	0.21228161448930424
11	HADOOP_JD	1.0803386076631785	0.28010741471430767
28	SQL_JD	-1.0694749311801401	0.2849706407566319
12	MACHINE_LEARNING_JD	1.0533258789399351	0.29230496417236573
25	SAP_JD	0.8917578915225491	0.372618239934996
20	POSTGRESQL_JD	0.8829626972510034	0.3773509202869031
7	COMPUTER_SCIENCE_JD	-0.7265696999473008	0.4675653088683164
15	MBA_JD	0.7103859042186884	0.47753861480581816
2	ARTIFICIAL_INTELLIGENCE_JD	0.5265208269355457	0.5985783757995188
5	BUSINESS_ANALYTICS_JD	0.4605549114369525	0.6451625534545673
3	AWS_JD	-0.38510341807958015	0.7001972604713105
23	REGRESSION_JD	0.26887987849240846	0.7880468171509017
6	CLUSTER_JD	-0.19727511747866192	0.8436301004915217
1	API_JD	0.17467062503652428	0.8613541938978051
8	ECONOMICS_JD	-0.018685437504887364	0.985093705098944
29	STATISTICS_JD	0.009878405231348503	0.9921191784794305

In [120]:

```
#Selecting keywords with p-value <0.1 into multiple regression model.
ttest_JD_pass1 = list(ttests_JD[ttests_JD['P-value'].astype(float)<0.1]['KW'])
print(*ttest_JD_pass1,sep=' + ')
```

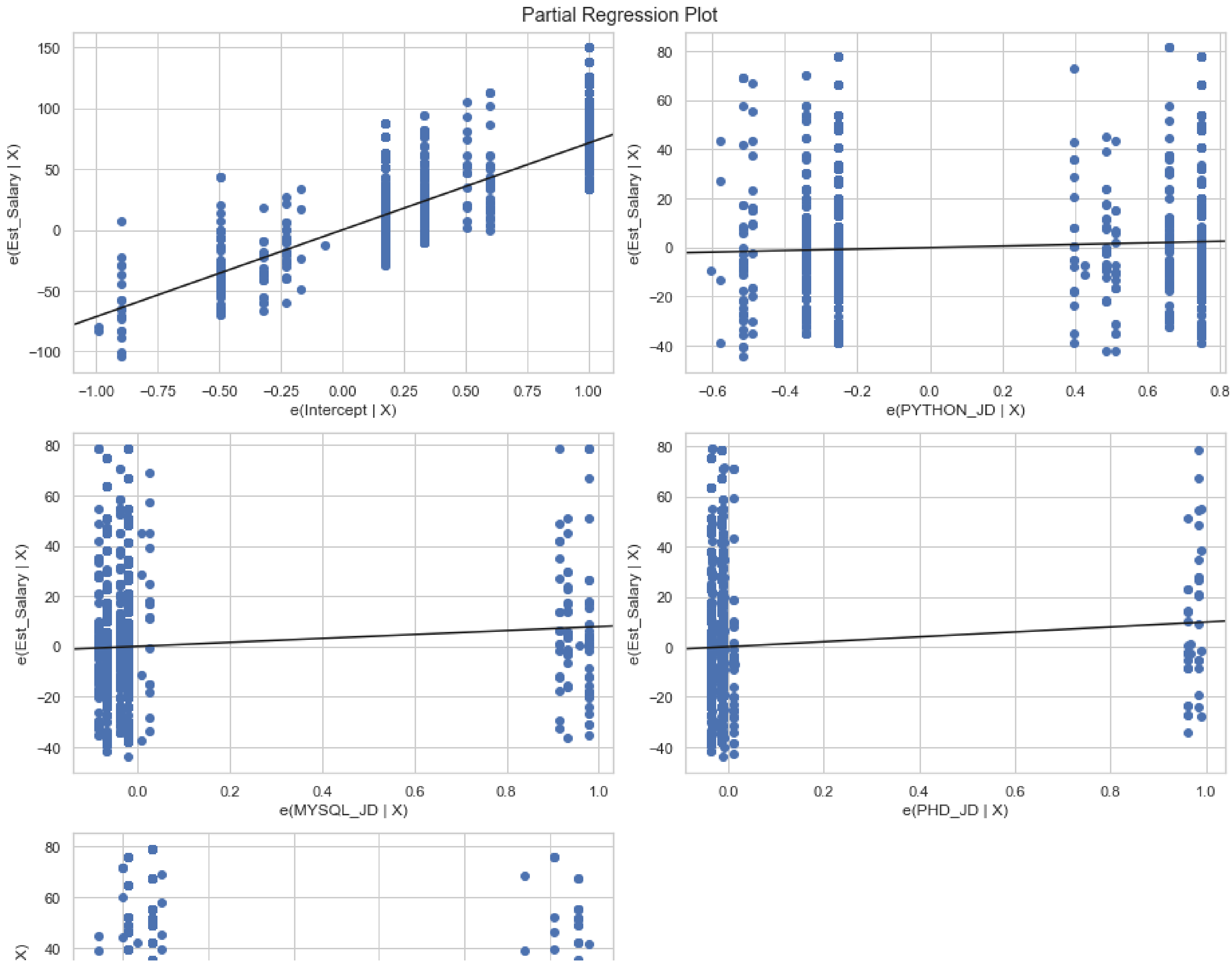
```
PYTHON_JD + MYSQL_JD + PHD_JD + SAS_JD + ORACLE_JD + MASTER_JD + ETL_JD
```

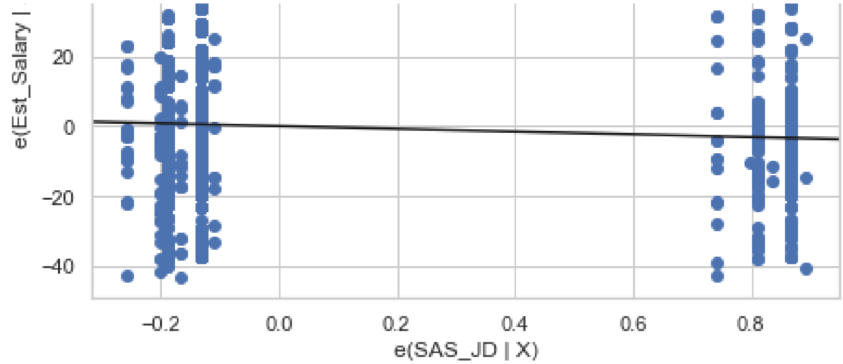
In [121]:
```
#Run regression and remove variables with p-value >0.05 one by one until all <0.05
JDMod = ols("Est_Salary ~ PYTHON_JD + MYSQL_JD + PHD_JD + SAS_JD",
               data=text_Analysis).fit()
print(JDMod.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.015
Model:                            OLS   Adj. R-squared:                  0.013
Method:                 Least Squares   F-statistic:                     8.371
Date:                Thu, 19 Nov 2020   Prob (F-statistic):           1.06e-06
Time:                        20:36:51   Log-Likelihood:                -10280.
No. Observations:                2248   AIC:                         2.057e+04
Df Residuals:                    2243   BIC:                         2.060e+04
Df Model:                           4
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     71.3701      0.617    115.606      0.000      70.159      72.581
PYTHON_JD      3.1417      1.112      2.824      0.005       0.960       5.323
MYSQL_JD       7.8541      2.659      2.954      0.003       2.640      13.068
PHD_JD         9.8404      3.583      2.747      0.006       2.815      16.866
SAS_JD        -3.9797      1.389     -2.865      0.004      -6.704      -1.256
==============================================================================
Omnibus:                      271.769   Durbin-Watson:                   0.078
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              392.985
Skew:                           0.898   Prob(JB):                     4.62e-86
Kurtosis:                       3.983   Cond. No.                         7.69
==============================================================================

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

this shows SAS analysts get paid lower.. this seems weird given niche nature of skill. If we look closer, its likely that these are for junior/entry level positions and/or at older (avg company age 38) firms in TX, one of the low-paying states. This didnt make to the final models where job location is controlled.

In [122]:
```
fig = plt.figure(figsize=(13, 13))
fig = sm.graphics.plot_partregress_grid(JDMod,fig=fig)
fig.tight_layout(pad=1.0)
```





Correlation: Job Location (State) vs Salary

In [123]:
```
# create dummy columns by State
kwdummy = pd.get_dummies(text_Analysis['State'].apply(pd.Series).stack()).sum(level=0)
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True,how='left').replace(np.nan,
```

In [124]:
```
S3 = text_Analysis['State'].value_counts().reset_index().rename(
    columns={'index':'State','State':'Count'})
S3_Top = S3[S3['Count']>29]
S3_Top
```

Out[124]:

	State	Count
0	CA	625
1	TX	394
2	NY	345
3	IL	164
4	PA	113
5	AZ	97
6	CO	95
7	NC	90
8	NJ	86
9	WA	53
10	VA	47
11	OH	35
12	UT	33

In [125]:
```
-test for top states hring analysts to see their correlation with salaries
olumns = list(text_Analysis.columns)
_state=[]
rd in text_columns:
 word in set(S3_Top['State']):
  ttest3 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                           text_Analysis[text_Analysis[word]==0]['Est_Salary'])
  ttests_state.append([word,ttest3])

_state = pd.DataFrame(ttests_state,columns=['State','R'])
_state['R']=ttests_state['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],['','',
_state['Statistic'],ttests_state['P-value']=ttests_state['R'].str.split(', ',1).str
_state=ttests_state.drop(['R'],axis=1).sort_values('P-value',ascending=True)
_state
```

```
<ipython-input-125-1ba7e1b4cc50>:12: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_state['Statistic'],ttests_state['P-value']=ttests_state['R'].str.split(', ',1).str
```

Out[125]:

	State	Statistic	P-value
3	IL	3.4871871764328914	0.0004975101658536639
12	WA	-2.3050985706606353	0.021251815764471424
11	VA	-1.982611386890212	0.047532516056225486
4	NC	-1.6508583728758894	0.09890730468575766
2	CO	0.6287405461537323	0.5295828637528285
6	NY	-0.6187817134630991	0.5361229211801275
0	AZ	-0.5741887677034088	0.5658975673027001
5	NJ	0.34616025876923495	0.7292547023228556
10	UT	-8.618507231442898	1.2572853439437861e-17
9	TX	-12.83231537576241	1.9913053850662446e-36
7	OH	-6.8713354197122065	8.207987823191773e-12
8	PA	-4.942682557049725	8.274789191649686e-07
1	CA	22.56089617442046	9.325868389127702e-102

In [126]:
```
#Selecting states with p-value <0.1 into multiple regression model.
ttest_state_pass = list(ttests_state[ttests_state['P-value'].astype(float)<0.1]['State'])
print(*ttest_state_pass,sep=' + ')
```

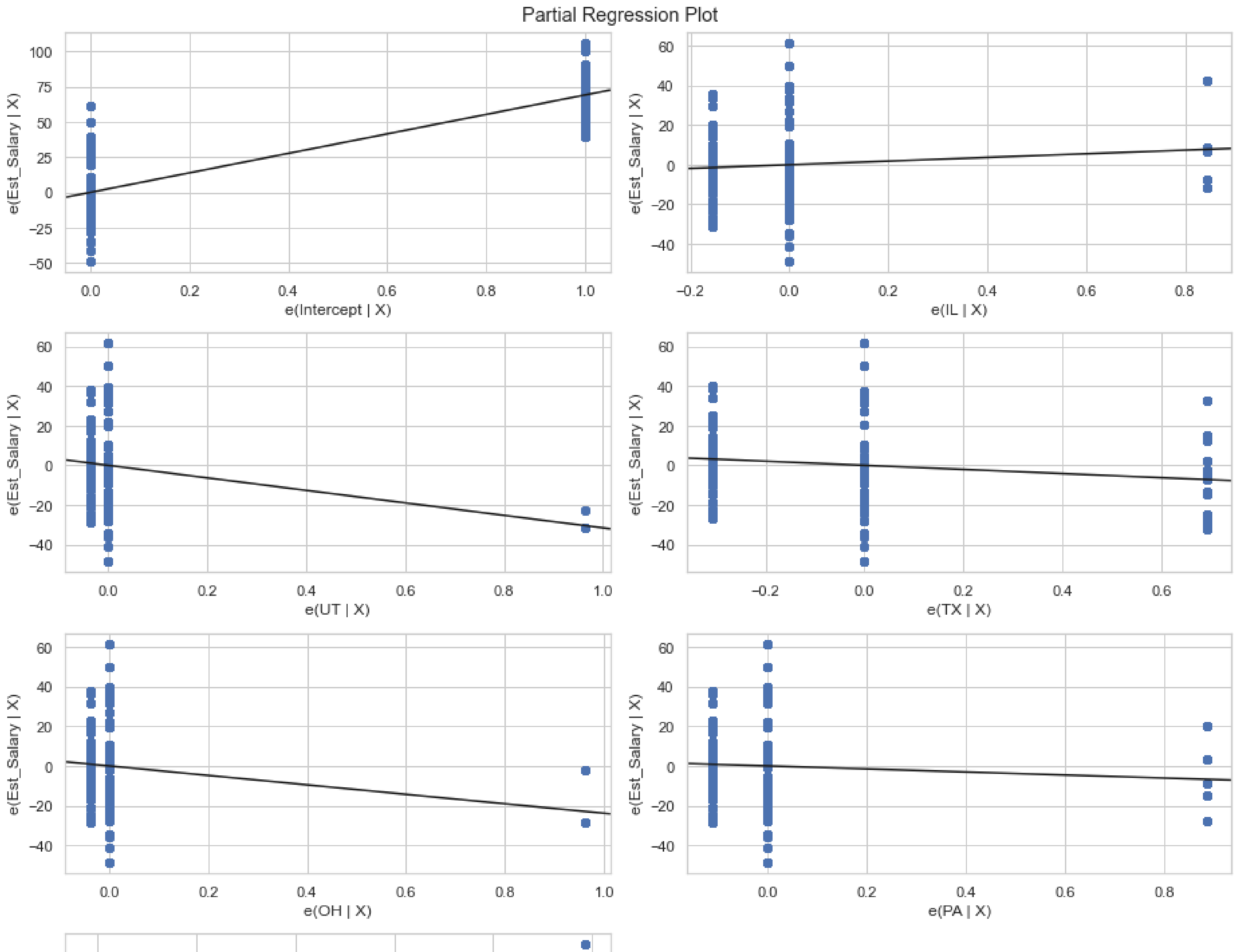
```
IL + WA + VA + NC + UT + TX + OH + PA + CA
```

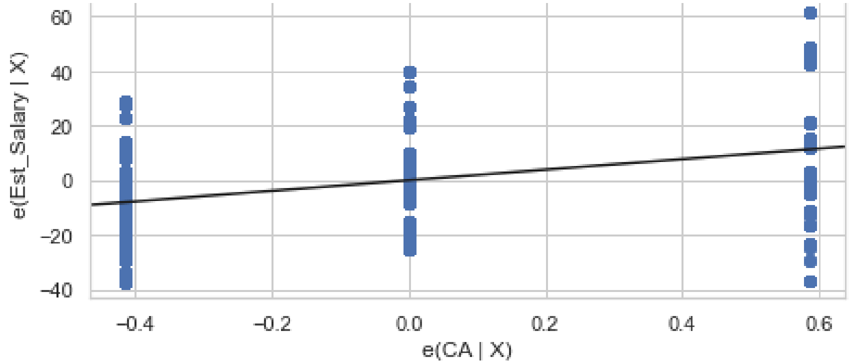
In [127]:
```
StateMod = ols("Est_Salary ~ IL + UT + TX + OH + PA + CA",
               data=text_Analysis).fit()
print(StateMod.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.263
Model:                            OLS   Adj. R-squared:                  0.261
Method:                 Least Squares   F-statistic:                     133.4
Date:                Thu, 19 Nov 2020   Prob (F-statistic):         1.03e-144
Time:                        20:51:56   Log-Likelihood:                -9953.7
No. Observations:                2248   AIC:                         1.992e+04
Df Residuals:                    2241   BIC:                         1.996e+04
Df Model:                           6
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     69.1131      0.683    101.247      0.000      67.774      70.452
IL             9.1979      1.726      5.330      0.000       5.814      12.582
UT           -31.5828      3.598     -8.777      0.000     -38.639     -24.526
TX           -10.3619      1.229     -8.428      0.000     -12.773      -7.951
OH           -23.9131      3.498     -6.837      0.000     -30.772     -17.054
PA            -7.6220      2.028     -3.759      0.000     -11.598      -3.646
CA            19.3741      1.061     18.266      0.000      17.294      21.454
==============================================================================
Omnibus:                      117.917   Durbin-Watson:                   0.065
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              139.853
Skew:                           0.550   Prob(JB):                     4.28e-31
Kurtosis:                       3.530   Cond. No.                         9.09
==============================================================================

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

job location is the most crucial factor to the salary variation - as we see from these results

In [128]:
```
fig = plt.figure(figsize=(13, 13))
fig = sm.graphics.plot_partregress_grid(StateMod,fig=fig)
fig.tight_layout(pad=1.0)
```





Correlation: HQ Location (State) vs Salary

In [129]:
```
S31 = text_Analysis['HQState'].value_counts().reset_index().rename(
    columns={'index':'HQState','HQState':'Count'}).replace(0,'Unknown_State')
S31_Top = S31[S31['Count']>29]
S31_Top['HQState_HQ'] = [s + '_HQ' for s in S31_Top['HQState']]
```

```
<ipython-input-129-78d26e763091>:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexin
g.html#returning-a-view-versus-a-copy)
  S31_Top['HQState_HQ'] = [s + '_HQ' for s in S31_Top['HQState']]
```

In [130]:
```
# create dummy columns by HQ State
kwdummy = pd.get_dummies(S31_Top['HQState_HQ'].apply(pd.Series).stack()).sum(level=0)
S31_Top2 = S31_Top.merge(kwdummy,left_index=True,right_index=True,how='left').drop(['Count'],axis=1)
text_Analysis = text_Analysis.merge(S31_Top2,on='HQState',how='left').replace(np.nan,0)
```

In [131]:

```
text_columns = list(text_Analysis.columns)
ttests_HQstate=[]
for word in text_columns:
    if word in set(S31_Top['HQState_HQ']):
        ttest31 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                                  text_Analysis[text_Analysis[word]==0]['Est_Salary'])
        ttests_HQstate.append([word,ttest31])

ttests_HQstate = pd.DataFrame(ttests_HQstate,columns=['HQState_HQ','R'])
ttests_HQstate['R']=ttests_HQstate['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)
ttests_HQstate['Statistic'],ttests_HQstate['P-value']=ttests_HQstate['R'].str.split(', ',1).str
ttests_HQstate=ttests_HQstate.drop(['R'],axis=1).sort_values('P-value',ascending=True)
ttests_HQstate
```

```
<ipython-input-131-ddfc8274281b>:11: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_HQstate['Statistic'],ttests_HQstate['P-value']=ttests_HQstate['R'].str.split(', ',1).str
```

Out[131]:

	HQState_HQ	Statistic	P-value
11	PA_HQ	-3.6037640030833424	0.0003204636663066424
10	OH_HQ	-2.9445101765893065	0.003267880764802911
8	NJ_HQ	2.8476438387769254	0.004444462296475872
9	NY_HQ	-2.803084277181425	0.005105106171003899
2	FL_HQ	-2.5318978889016837	0.011412349249393593
14	VA_HQ	-1.6758265887843584	0.09391134990189316
7	NC_HQ	-1.5133419727523838	0.13033351230166712
6	MI_HQ	1.4159906541479472	0.15691689954508944
4	IL_HQ	-1.003654468297828	0.3156533057185176
15	WA_HQ	-0.3794687224420757	0.7043757000332287
0	AZ_HQ	-0.2417531879742219	0.8089934832140739
5	MD_HQ	-0.10379942916209027	0.9173377868348767
3	GA_HQ	0.040143815982733824	0.967982037746448
1	CA_HQ	11.45806752715845	1.3973500107699286e-29

	HQState_HQ	Statistic	P-value
12	TX_HQ	-5.377454789131364	8.337413418129029e-08
13	Unknown_State_HQ	nan	nan

In [132]:
```
ttest_HQstate_pass = list(ttests_HQstate[ttests_HQstate['P-value'].astype(float)<0.1]['HQState_HQ'])
print(*ttest_HQstate_pass,sep=' + ')
```

```
PA_HQ + OH_HQ + NJ_HQ + NY_HQ + FL_HQ + VA_HQ + CA_HQ + TX_HQ
```

In [133]:
```
HQStateMod = ols("Est_Salary ~ PA_HQ + OH_HQ + NJ_HQ + CA_HQ + TX_HQ",
               data=text_Analysis).fit()
print(HQStateMod.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.074
Model:                            OLS   Adj. R-squared:                  0.072
Method:                 Least Squares   F-statistic:                     35.81
Date:                Thu, 19 Nov 2020   Prob (F-statistic):           2.29e-35
Time:                        20:54:04   Log-Likelihood:                -10211.
No. Observations:                2248   AIC:                         2.043e+04
Df Residuals:                    2242   BIC:                         2.047e+04
Df Model:                           5
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     69.7920      0.626    111.551      0.000      68.565      71.019
PA_HQ         -6.6861      2.545     -2.627      0.009     -11.678      -1.694
OH_HQ         -9.8389      4.070     -2.418      0.016     -17.820      -1.858
NJ_HQ          7.3909      1.883      3.924      0.000       3.698      11.084
CA_HQ         13.2069      1.226     10.768      0.000      10.802      15.612
TX_HQ         -6.6781      1.807     -3.695      0.000     -10.222      -3.134
==============================================================================
Omnibus:                      233.094   Durbin-Watson:                   0.165
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              320.219
Skew:                           0.820   Prob(JB):                     2.92e-70
Kurtosis:                       3.856   Cond. No.                         8.76
==============================================================================

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

CA, and NJ headquartered companies pay more

Addnl Variables: Revenue, Size, Sector, Industry and Type of Ownership

In [134]:
```
#Remove special characters.
text_Analysis['Revenue_USD'] = text_Analysis['Revenue_USD'].replace('[^A-Za-z0-9]+', '_',regex=True).rep
text_Analysis['Size'] = text_Analysis['Size'].replace('[^A-Za-z0-9]+', '_',regex=True).replace(
    '10000_employees','Large_Firm').replace('Unknown','SizeUnknown')
text_Analysis['Sector'] = text_Analysis['Sector'].replace('[^A-Za-z0-9]+', '_',regex=True).replace(['Gov
text_Analysis['Industry'] = text_Analysis['Industry'].replace('[^A-Za-z0-9]+', '_',regex=True).replace('
text_Analysis['Type of ownership'] = text_Analysis['Type of ownership'].replace('[^A-Za-z0-9]+', '_',reg
```

In [135]:
```
#Rename column name for running regression later.
text_Analysis = text_Analysis.rename(columns={"Easy Apply":"Easy_Apply"})
```

To run multiple regression, will create revenue variables

In [136]:
```
# create dummy columns by Revenue
kwdummy = pd.get_dummies(text_Analysis['Revenue_USD'].apply(pd.Series).stack()).sum(level=0)
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True,how='left').replace(np.nan,
```

In [137]:
```
S4 = text_Analysis['Revenue_USD'].value_counts().reset_index().rename(
    columns={'index':'Revenue_USD','Revenue_USD':'Count'})
S4_Top = S4[S4['Count']>29]
S4_Top
```

Out[137]:

	Revenue_USD	Count
0	RevUnknown	614
1	100_500_million	218
2	50_100_million	199
3	10_billion	189
4	0	163
5	10_25_million	131
6	2_5_billion	128
7	Small_Business	110
8	25_50_million	109
9	_1_million	93
10	1_2_billion	87
11	0_5_1_billion	79
12	5_10_million	72
13	5_10_billion	56

we will ignore Revenue '0' (these are NaN replaced values)

In [138]:
```
run t-test to see the salary differences by companies' revenue.
ext_columns = list(text_Analysis.columns)
tests_rev=[]
or word in text_columns:
   if word in set(S4_Top['Revenue_USD']):
       ttest4 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                                text_Analysis[text_Analysis[word]==0]['Est_Salary'])
       ttests_rev.append([word,ttest4])

tests_rev = pd.DataFrame(ttests_rev,columns=['Revenue_USD','R'])
tests_rev['R']=ttests_rev['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],['',''
tests_rev['Statistic'],ttests_rev['P-value']=ttests_rev['R'].str.split(', ',1).str
tests_rev=ttests_rev.drop(['R'],axis=1).sort_values('P-value',ascending=True)
tests_rev
```

```
<ipython-input-138-f2c00b869e91>:12: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_rev['Statistic'],ttests_rev['P-value']=ttests_rev['R'].str.split(', ',1).str
```

Out[138]:

	Revenue_USD	Statistic	P-value
8	50_100_million	-2.067317153187129	0.03881858844357256
12	Small_Business	1.7920605706297863	0.07325782185970323
11	RevUnknown	1.7153964943524806	0.08641048104727897
6	25_50_million	1.1404777581168355	0.25420891071519525
4	10_billion	-1.0206924598208893	0.307510095279054
1	0_5_1_billion	-0.8837686030458463	0.3769157267568668
0	0	0.7487984635216214	0.4540570941766361
3	10_25_million	-0.7348420252780572	0.4625124256896209
5	1_2_billion	-0.7282929831891864	0.46651017904869185
10	5_10_million	-0.615018504932283	0.5386048038973348
13	_1_million	-0.5139139677166249	0.6073626965182952
9	5_10_billion	0.5123603181347793	0.6084492364095251
7	2_5_billion	-0.23253042729886442	0.8161472434253468

	Revenue_USD	Statistic	P-value
2	100_500_million	-0.20076780574360448	0.8408983157364056

this seems weird, that medium businesses (50-100 million) pays 2K less than average as small business pays more. this is to be analysed for validity in multiple regression later

In [139]:
```
#Selecting revenues with p-value <0.1 into multiple regression model.
ttest_rev_pass = list(ttests_rev[ttests_rev['P-value'].astype(float)<0.1]['Revenue_USD'])
print(*ttest_rev_pass,sep=' + ')
```

```
50_100_million + Small_Business + RevUnknown
```

To run multiple regression, will create size variables

In [140]:
```
kwdummy = pd.get_dummies(text_Analysis['Size'].apply(pd.Series).stack()).sum(level=0)
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True,how='left').replace(np.nan,
```

In [141]:
```
S5 = text_Analysis['Size'].value_counts().reset_index().rename(
    columns={'index':'Size','Size':'Count'})
S5_Top = S5[S5['Count']>29]
S5_Top
```

Out[141]:

	Size	Count
0	51_to_200_employees	419
1	Large_Firm	374
2	1001_to_5000_employees	348
3	1_to_50_employees	346
4	201_to_500_employees	248
5	501_to_1000_employees	211
6	0	163
7	5001_to_10000_employees	97
8	SizeUnknown	42

'0' are NaN values replaced for making dummy columns, to be ignored

In [142]:
```
text_columns = list(text_Analysis.columns)
ttests_size=[]
for word in text_columns:
    if word in set(S5_Top['Size']):
        ttest5 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                                 text_Analysis[text_Analysis[word]==0]['Est_Salary'])
        ttests_size.append([word,ttest5])

ttests_size = pd.DataFrame(ttests_size,columns=['Size','R'])
ttests_size['R']=ttests_size['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],[''
ttests_size['Statistic'],ttests_size['P-value']=ttests_size['R'].str.split(', ',1).str
ttests_size=ttests_size.drop(['R'],axis=1).sort_values('P-value',ascending=True)
ttests_size
```

```
<ipython-input-142-9a4ae35ab2cf>:11: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_size['Statistic'],ttests_size['P-value']=ttests_size['R'].str.split(', ',1).str
```

Out[142]:

	Size	Statistic	P-value
6	Large_Firm	-1.9996311944650396	0.04566035288352724
3	5001_to_10000_employees	0.8807204375971571	0.37856338271610757
0	1001_to_5000_employees	0.630499072016383	0.5284322542135438
2	201_to_500_employees	-0.6231434207771377	0.5332535472070133
1	1_to_50_employees	0.5398365152487532	0.589363298961973
5	51_to_200_employees	0.39500587582528507	0.6928760604548097
7	SizeUnknown	0.12736017744573036	0.898666734369518
4	501_to_1000_employees	-0.09517249730174987	0.9241863047596062

p-value indicates that it is statistically significant that larger firms seem to pay 2K less than average sized companies

In [143]:
```
ttest_size_pass = list(ttests_size[ttests_size['P-value'].astype(float)<0.1]['Size'])
print(*ttest_size_pass,sep=' + ')
```

```
Large_Firm
```

To run multiple regression, will create sector variables

In [144]:
```
kwdummy = pd.get_dummies(text_Analysis['Sector'].apply(pd.Series).stack()).sum(level=0)
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True,how='left').replace(np.nan,
```

In [145]:
```
S6 = text_Analysis['Sector'].value_counts().reset_index().rename(
    columns={'index':'Sector','Sector':'Count'})
S6_Top = S6[S6['Count']>29]
S6_Top
```

Out[145]:

	Sector	Count
0	Information_Technology	570
1	Business_Services	521
2	0	352
3	Finance	169
4	Health_Care	151
5	Education	52
6	Insurance	51
7	Accounting_Legal	43
8	Media	42
9	Manufacturing	40
10	Retail	38
11	GovSec	36
12	Biotech_Pharmaceuticals	32

In [146]:
```
text_columns = list(text_Analysis.columns)
ttests_sec=[]
for word in text_columns:
    if word in set(S6_Top['Sector']):
        ttest6 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                                 text_Analysis[text_Analysis[word]==0]['Est_Salary'])
        ttests_sec.append([word,ttest6])

ttests_sec = pd.DataFrame(ttests_sec,columns=['Sector','R'])
ttests_sec['R']=ttests_sec['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],['','
ttests_sec['Statistic'],ttests_sec['P-value']=ttests_sec['R'].str.split(', ',1).str
ttests_sec=ttests_sec.drop(['R'],axis=1).sort_values('P-value',ascending=True)
ttests_sec
```

```
<ipython-input-146-b8d294e055ea>:11: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_sec['Statistic'],ttests_sec['P-value']=ttests_sec['R'].str.split(', ',1).str
```

Out[146]:

	Sector	Statistic	P-value
2	Biotech_Pharmaceuticals	2.609814640539972	0.009119299299076195
5	Finance	-2.5739778621517253	0.010117235084272815
8	Information_Technology	2.474371774473128	0.013420443361020702
6	GovSec	-2.003491440722664	0.04524449027957346
12	Retail	-1.4356428089942357	0.15124325511231285
11	Media	-1.013843460043587	0.31076665658090963
1	Accounting_Legal	0.8651283135577105	0.3870607584609026
4	Education	-0.7934546030374406	0.4275968223954776
9	Insurance	-0.5752324092567795	0.5651917466545469
0	0	0.5340640495804618	0.5933500751606593
7	Health_Care	0.3622812866735705	0.7171759245445649
3	Business_Services	0.20831305604019493	0.8350034260690025
10	Manufacturing	-0.016334642726151673	0.9869688711457016

Biotech, Pharma and IT are the highest paying sectors ; Fiance and Govts pay less

In [147]:
```
ttest_sec_pass = list(ttests_sec[ttests_sec['P-value'].astype(float)<0.1]['Sector'])
print(*ttest_sec_pass,sep=' + ')
```

```
Biotech_Pharmaceuticals + Finance + Information_Technology + GovSec
```

To run multiple regression, will create IT Industries variables

i found out later that only IT is statistically signifcant in the final regression model, so dig deeper into the subcategory "industry" under the IT sector

In [148]:
```
kwdummy = pd.get_dummies(text_Analysis[text_Analysis['Sector']=='Information_Technology']['Industry'].ap
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True,how='left').replace(np.nan,
```

In [149]:
```
S7 = text_Analysis[text_Analysis['Sector']=='Information_Technology']['Industry'].value_counts().reset_i
    columns={'index':'Industry','Industry':'Count'})
S7_Top = S7[S7['Count']>29]
S7_Top
```

Out[149]:

	Industry	Count
0	IT_Services	325
1	Computer_Hardware_Software	111
2	Enterprise_Software_Network_Solutions	69
3	Internet	65

In [150]:
```
text_columns = list(text_Analysis.columns)
ttests_ind=[]
for word in text_columns:
    if word in set(S7_Top['Industry']):
        ttest7 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                                 text_Analysis[text_Analysis[word]==0]['Est_Salary'])
        ttests_ind.append([word,ttest7])

ttests_ind = pd.DataFrame(ttests_ind,columns=['Industry','R'])
ttests_ind['R']=ttests_ind['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],['','
ttests_ind['Statistic'],ttests_ind['P-value']=ttests_ind['R'].str.split(', ',1).str
ttests_ind=ttests_ind.drop(['R'],axis=1).sort_values('P-value',ascending=True)
ttests_ind
```

```
<ipython-input-150-502f5f69eabb>:11: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_ind['Statistic'],ttests_ind['P-value']=ttests_ind['R'].str.split(', ',1).str
```

Out[150]:

	Industry	Statistic	P-value
3	Internet	2.6110371303049753	0.009086864742848826
0	Computer_Hardware_Software	2.5260073048249203	0.011604934226911195
1	Enterprise_Software_Network_Solutions	1.8556879665956705	0.06362895900206361
2	IT_Services	-0.6489249573131813	0.5164532282392558

most industries in IT sector pay more

In [151]:
```
ttest_ind_pass = list(ttests_ind[ttests_ind['P-value'].astype(float)<0.1]['Industry'])
print(*ttest_ind_pass,sep=' + ')
```

```
Internet + Computer_Hardware_Software + Enterprise_Software_Network_Solutions
```

To run multiple regression, will create Ownership variables

In [152]:
```
kwdummy = pd.get_dummies(text_Analysis['Type of ownership'].apply(pd.Series).stack()).sum(level=0)
text_Analysis = text_Analysis.merge(kwdummy,left_index=True,right_index=True,how='left').replace(np.nan,
```

In [153]:
```
S8 = text_Analysis['Type of ownership'].value_counts().reset_index().rename(
    columns={'index':'Type_of_ownership','Type of ownership':'Count'})
S8_Top = S8[S8['Count']>29]
S8_Top
```

Out[153]:

	Type_of_ownership	Count
0	Company_Private	1268
1	Company_Public	452
2	0	163
3	Nonprofit_Organization	124
4	Subsidiary_or_Business_Segment	89
5	Government	37
6	College_University	34

In [154]:
```
text_columns = list(text_Analysis.columns)
ttests_own=[]
for word in text_columns:
    if word in set(S8_Top['Type_of_ownership']):
        ttest8 = stats.ttest_ind(text_Analysis[text_Analysis[word]>0]['Est_Salary'],
                                 text_Analysis[text_Analysis[word]==0]['Est_Salary'])
        ttests_own.append([word,ttest8])

ttests_own = pd.DataFrame(ttests_own,columns=['Type_of_ownership','R'])
ttests_own['R']=ttests_own['R'].astype(str).replace(['Ttest_indResult\(statistic=','pvalue=','\)'],['','
ttests_own['Statistic'],ttests_own['P-value']=ttests_own['R'].str.split(', ',1).str
ttests_own=ttests_own.drop(['R'],axis=1).sort_values('P-value',ascending=True)
ttests_own
```

```
<ipython-input-154-0dd02120d9ba>:11: FutureWarning: Columnar iteration over characters will be depreca
ted in future releases.
  ttests_own['Statistic'],ttests_own['P-value']=ttests_own['R'].str.split(', ',1).str
```

Out[154]:

	Type_of_ownership	Statistic	P-value
3	Government	-3.0701964982979657	0.0021647848363638695
4	Nonprofit_Organization	-1.703857781949545	0.0885459857780986
1	Company_Private	0.8848239369765997	0.37634630926402446
5	Subsidiary_or_Business_Segment	-0.7078924103974973	0.47908552437246077
2	Company_Public	0.5699318976535838	0.5687808905981325
0	College_University	0.2992278900437682	0.7647938555194423

NGOs look like paying less

In [155]:
```
ttest_own_pass = list(ttests_own[ttests_own['P-value'].astype(float)<0.1]['Type_of_ownership'])
print(*ttest_own_pass,sep=' + ')
```

```
Government + Nonprofit_Organization
```

Final Regression Model

In [ ]:
```
before considering interaction terms , combined regression model
```

In [156]:
```
ModC = ols("Est_Salary ~ JUNIOR + IL + UT + TX + OH + PA + CA + Small_Business + Information_Technology
                data=text_Analysis).fit()
# Rating, Years_Founded, Easy_Apply, PHD, Sector, Size, Type_of_ownership not significant
print(ModC.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.275
Model:                            OLS   Adj. R-squared:                  0.271
Method:                 Least Squares   F-statistic:                     77.05
Date:                Thu, 19 Nov 2020   Prob (F-statistic):          2.72e-147
Time:                        21:18:06   Log-Likelihood:                -9935.7
No. Observations:                2248   AIC:                         1.990e+04
Df Residuals:                    2236   BIC:                         1.996e+04
Df Model:                          11
Covariance Type:            nonrobust
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
Intercept                 68.0896      0.742     91.720      0.000      66.634      69.545
JUNIOR                    -8.2066      2.484     -3.304      0.001     -13.078      -3.335
IL                         9.7640      1.719      5.681      0.000       6.393      13.135
UT                       -31.2224      3.579     -8.724      0.000     -38.240     -24.204
TX                       -10.2908      1.223     -8.414      0.000     -12.689      -7.892
OH                       -23.2337      3.477     -6.683      0.000     -30.052     -16.416
PA                        -7.4972      2.016     -3.718      0.000     -11.451      -3.543
CA                        19.2809      1.060     18.182      0.000      17.201      21.360
Small_Business             4.5334      1.981      2.288      0.022       0.648       8.419
Information_Technology     1.7674      1.003      1.762      0.078      -0.199       3.734
NJ_HQ                      5.2514      1.661      3.161      0.002       1.994       8.509
MYSQL_JD                   4.8251      2.280      2.116      0.034       0.353       9.297
==============================================================================
Omnibus:                      121.099   Durbin-Watson:                   0.092
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              143.994
Skew:                           0.560   Prob(JB):                     5.40e-32
Kurtosis:                       3.532   Cond. No.                         9.46
==============================================================================

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

In [157]:
```
# Trying different interaction terms.
text_Analysis['CA_SB']=text_Analysis['CA']*text_Analysis['Small_Business']
text_Analysis['CA_IT']=text_Analysis['CA']*text_Analysis['Information_Technology']
text_Analysis['IT_SB']=text_Analysis['Information_Technology']*text_Analysis['Small_Business']
text_Analysis['CA_IT_SB']=text_Analysis['Information_Technology']*text_Analysis['Small_Business']*text_A
text_Analysis['CA_NJ_HQ']=text_Analysis['CA']*text_Analysis['NJ_HQ']
text_Analysis['SB_NJ_HQ']=text_Analysis['Small_Business']*text_Analysis['NJ_HQ']
text_Analysis['IT_NJ_HQ']=text_Analysis['Information_Technology']*text_Analysis['NJ_HQ']
text_Analysis['CA_PHD']=text_Analysis['CA']*text_Analysis['PHD_JD']
text_Analysis['CA_CA_HQ']=text_Analysis['CA']*text_Analysis['CA_HQ']
```

In [158]:
```
ModS = ols("Est_Salary ~ CA + CA_PHD + PHD_JD",
               data=text_Analysis).fit()
print(ModS.summary())
```

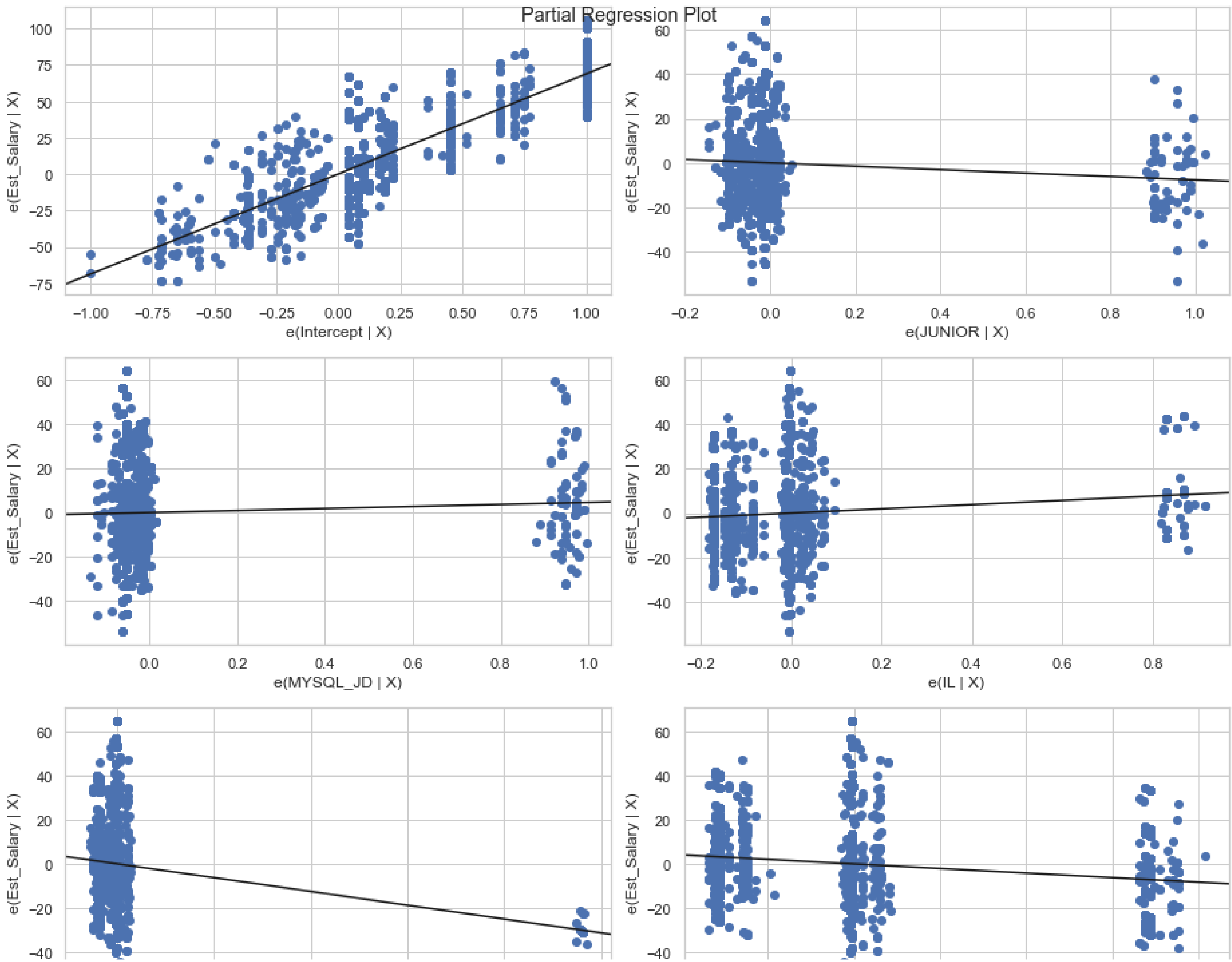
```
                            OLS Regression Results
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.186
Model:                            OLS   Adj. R-squared:                  0.185
Method:                 Least Squares   F-statistic:                     171.1
Date:                Thu, 19 Nov 2020   Prob (F-statistic):          6.66e-100
Time:                        21:18:29   Log-Likelihood:                -10065.
No. Observations:                2248   AIC:                         2.014e+04
Df Residuals:                    2244   BIC:                         2.016e+04
Df Model:                           3
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
Intercept     65.8195      0.533    123.553      0.000      64.775      66.864
CA            22.3480      1.018     21.943      0.000      20.351      24.345
CA_PHD         7.6747      6.507      1.179      0.238      -5.086      20.435
PHD_JD         1.4078      4.576      0.308      0.758      -7.565      10.381
==============================================================================
Omnibus:                       83.449   Durbin-Watson:                   0.063
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               92.315
Skew:                           0.476   Prob(JB):                     9.00e-21
Kurtosis:                       3.284   Cond. No.                         17.3
==============================================================================

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

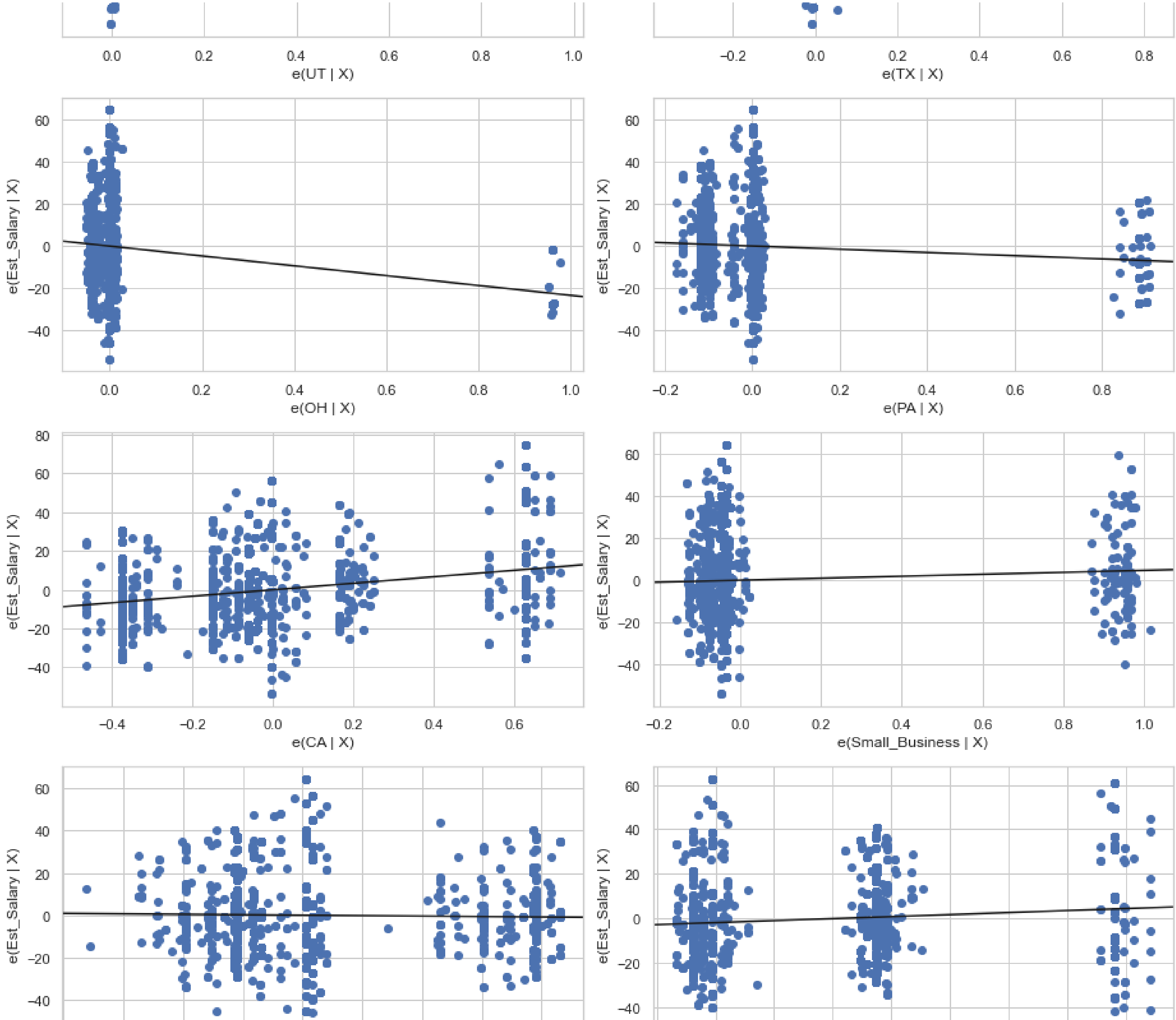
In [159]:
```python
# Final model considering interaction terms.
ModC = ols("Est_Salary ~ JUNIOR + MYSQL_JD + IL + UT + TX + OH + PA + CA + Small_Business + Information_
            data=text_Analysis).fit()
# Rating, Years_Founded, Easy_Apply, PHD, Sector, Size, Type_of_ownership not significant
print(ModC.summary())
```

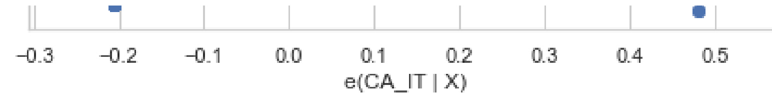
```
                            OLS Regression Results                            
==============================================================================
Dep. Variable:             Est_Salary   R-squared:                       0.281
Model:                            OLS   Adj. R-squared:                  0.277
Method:                 Least Squares   F-statistic:                     72.68
Date:                Thu, 19 Nov 2020   Prob (F-statistic):          3.32e-150
Time:                        21:18:39   Log-Likelihood:                -9926.7
No. Observations:                2248   AIC:                         1.988e+04
Df Residuals:                    2235   BIC:                         1.995e+04
Df Model:                          12                                         
Covariance Type:            nonrobust                                         
==========================================================================================
                             coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------------------
Intercept                 68.7600      0.756     90.934      0.000      67.277      70.243
JUNIOR                    -7.6660      2.478     -3.094      0.002     -12.525      -2.807
MYSQL_JD                   4.5965      2.272      2.023      0.043       0.140       9.053
IL                         9.5193      1.713      5.556      0.000       6.160      12.879
UT                       -31.1279      3.565     -8.731      0.000     -38.119     -24.136
TX                       -10.2760      1.218     -8.434      0.000     -12.665      -7.887
OH                       -23.3006      3.464     -6.727      0.000     -30.093     -16.508
PA                        -7.6452      2.009     -3.806      0.000     -11.585      -3.706
CA                        16.7653      1.211     13.848      0.000      14.391      19.139
Small_Business             4.6644      1.974      2.363      0.018       0.793       8.536
Information_Technology    -1.0613      1.200     -0.884      0.377      -3.415       1.292
CA_IT                      9.0154      2.120      4.253      0.000       4.859      13.172
NJ_HQ                      5.4123      1.655      3.270      0.001       2.166       8.658
==============================================================================
Omnibus:                      120.840   Durbin-Watson:                   0.108
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              143.196
Skew:                           0.562   Prob(JB):                     8.04e-32
Kurtosis:                       3.517   Cond. No.                         9.51
==============================================================================

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

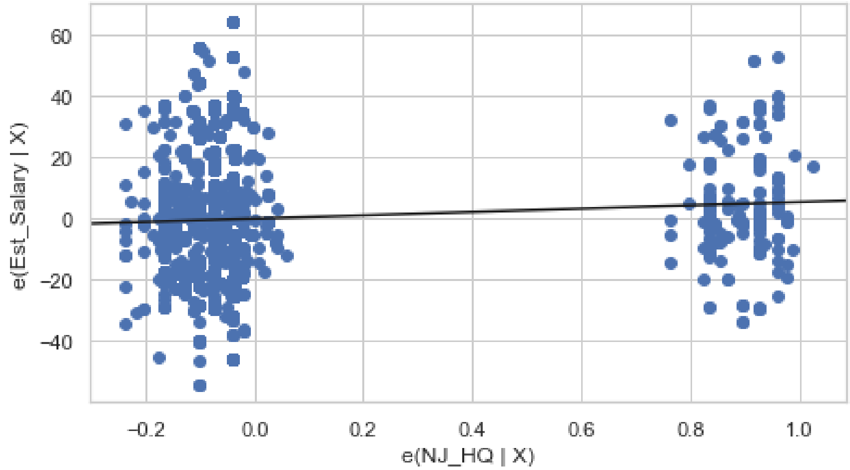
- job location is the most important factor behind salary variations
- IT companies don't seem to be paying more always, but CA IT firms definitely do.
- business with 1 to 5 million revenue USD tend to pay more
- higher pay for NJ headquartered companies
- MYSQL experience analysts have higher pay
- PHD didn't make it to the final model, nor did the interaction term "CA_PHD"

In [160]:
```
fig = plt.figure(figsize=(13, 26))
fig = sm.graphics.plot_partregress_grid(ModC,fig=fig)
fig.tight_layout(pad=1.0)
```




e(UT | X)
e(TX | X)
e(Est_Salary | X)
e(OH | X)
e(Est_Salary | X)
e(PA | X)
e(Est_Salary | X)
e(CA | X)
e(Est_Salary | X)
e(Small_Business | X)
e(Est_Salary | X)
e(Est_Salary | X)





California Salary Distribution

In [161]:
```
# create a separate dataset for CA
data_CA = data[data['State']=='CA']
```

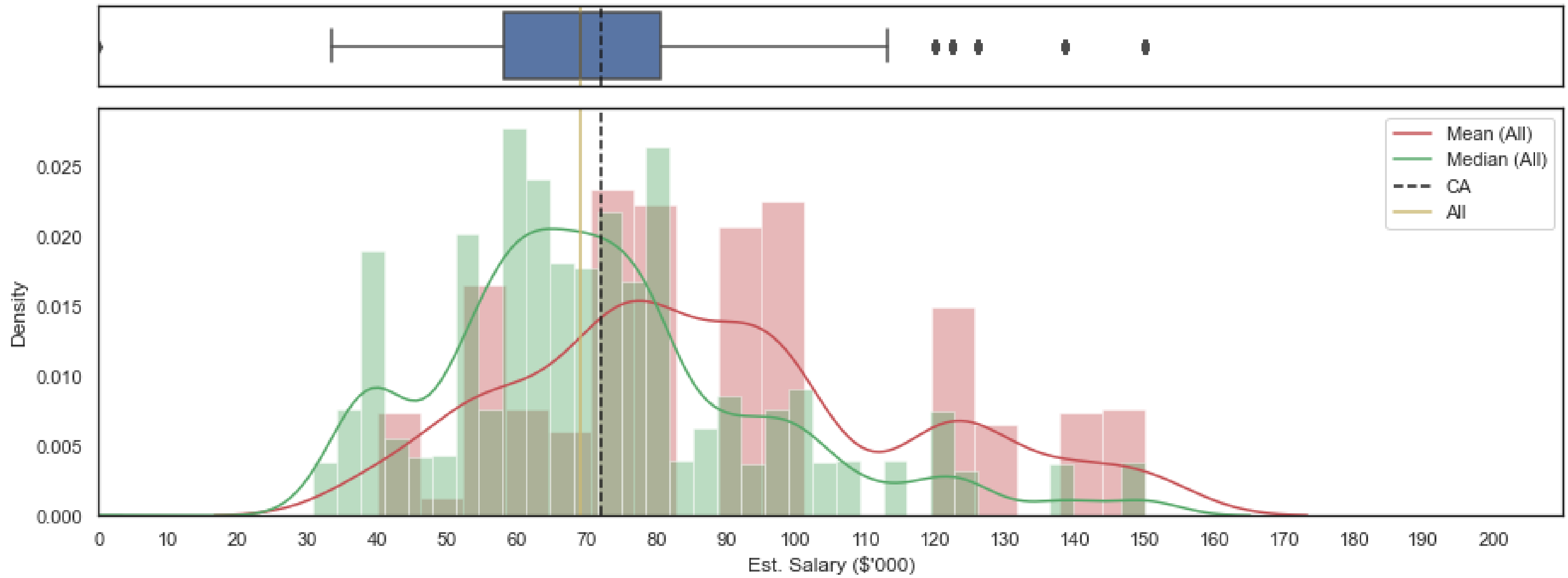
In [162]:
```
pd.set_option('display.max_columns', None)
data_CA.describe(include='all')
```

Out[162]:

	Unnamed: 0	Job Title	Job Description	Rating	Company Name	Location	Headquarters	Size	Founded	Type of ownership	Industr
count	626.000000	626	626	547.000000	626	626	579	582	448.000000	582	51
unique	NaN	373	626	NaN	474	74	179	8	NaN	12	5
top	NaN	Data Analyst	Job Description\nThe Data Analyst will need to...	NaN	Staffigo Technical Services, LLC	San Francisco, CA	San Francisco, CA	51 to 200 employees	NaN	Company - Private	I Service
freq	NaN	121	1	NaN	12	119	56	129	NaN	361	8
mean	1335.696486	NaN	NaN	3.849909	NaN	NaN	NaN	NaN	1988.792411	NaN	Na
std	559.938274	NaN	NaN	0.601810	NaN	NaN	NaN	NaN	34.319713	NaN	Na
min	454.000000	NaN	NaN	1.000000	NaN	NaN	NaN	NaN	1682.000000	NaN	Na
25%	666.250000	NaN	NaN	3.450000	NaN	NaN	NaN	NaN	1982.000000	NaN	Na
50%	1506.500000	NaN	NaN	3.900000	NaN	NaN	NaN	NaN	2000.000000	NaN	Na
75%	1915.750000	NaN	NaN	4.100000	NaN	NaN	NaN	NaN	2009.000000	NaN	Na
max	2072.000000	NaN	NaN	5.000000	NaN	NaN	NaN	NaN	2019.000000	NaN	Na

In [163]:
```
sns.set(style='white')

f, (ax_box, ax_hist) = plt.subplots(2, sharex=True, gridspec_kw= {"height_ratios": (0.2, 1)},figsize=(13
mean=data['Est_Salary'].mean()
median=data['Est_Salary'].median()

bph = sns.boxplot(data['Est_Salary'], ax=ax_box).set(xlabel="")
ax_box.axvline(mean, color='k', linestyle='--')
ax_box.axvline(median, color='y', linestyle='-')

dp1 = sns.distplot(data_CA['Est_Salary'],ax=ax_hist, color="r").set(xlabel="Est. Salary ($'000)")
dp2 = sns.distplot(data['Est_Salary'],ax=ax_hist, color="g").set(xlabel="Est. Salary ($'000)")
ax_hist.axvline(mean, color='k', linestyle='--')
ax_hist.axvline(median, color='y', linestyle='-')

plt.legend({'Mean (All)':mean,'Median (All)':median,'CA':data_CA['Est_Salary'],'All':data['Est_Salary']}
plt.xlim(0,210)
plt.xticks(np.arange(0,210,step=10))
plt.tight_layout() #Adjust the padding between and around subplots
plt.show()
```

```
/usr/local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following va
riable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and
passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(
/usr/local/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a d
eprecated function and will be removed in a future version. Please adapt your code to use either `disp
lot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for hist
ograms).
  warnings.warn(msg, FutureWarning)
/usr/local/lib/python3.8/site-packages/seaborn/distributions.py:2551: FutureWarning: `distplot` is a d
eprecated function and will be removed in a future version. Please adapt your code to use either `disp
lot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for hist
ograms).
  warnings.warn(msg, FutureWarning)
```

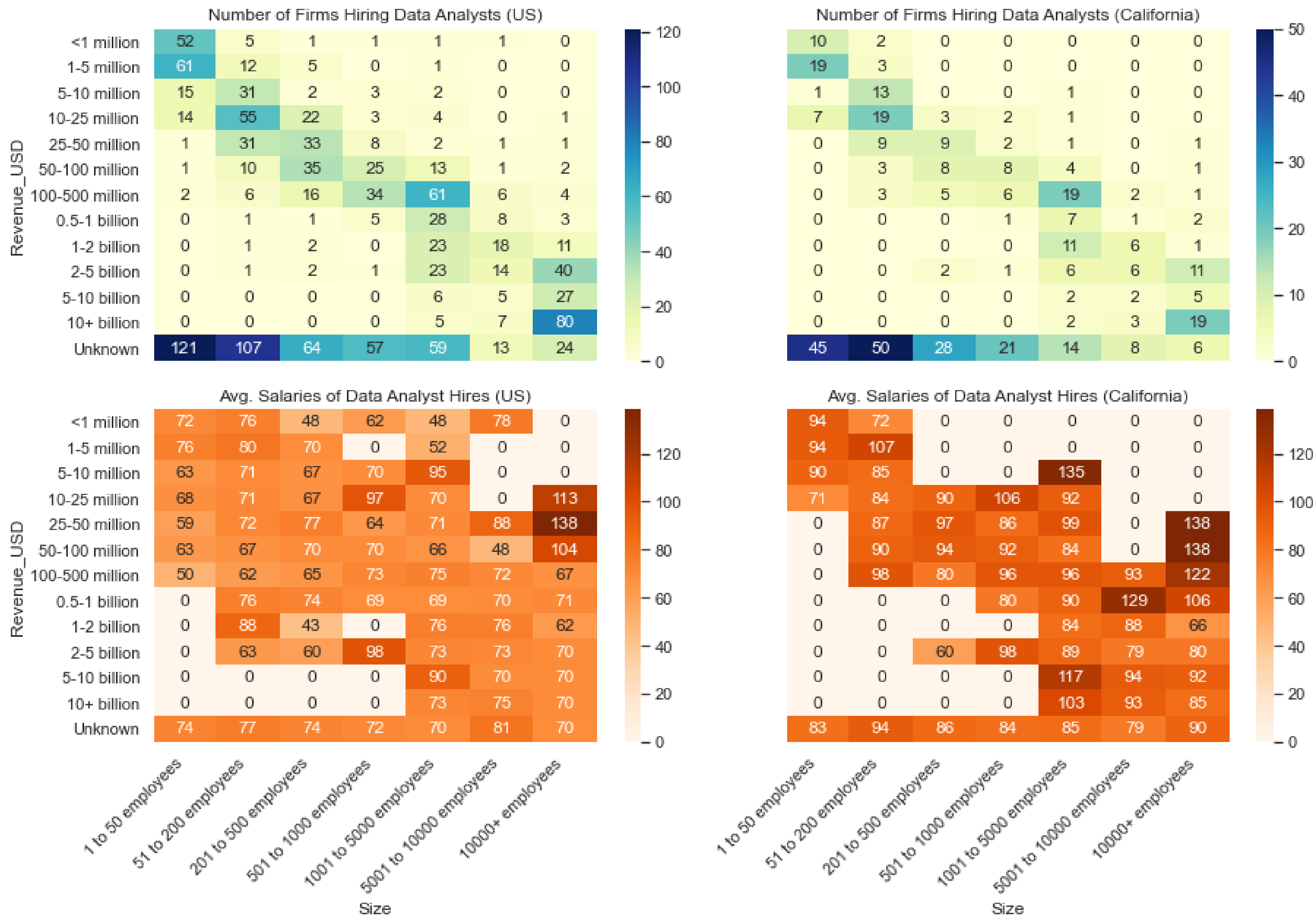


when compared to US entirely, salary distribution for CA shifts to right, indicating higher salary levels for CA

[Heatmap] California vs ALL - Number, Size and Salary of Hiring Firms

In [164]:
```
# Create a table for heatmap of number of companies with different sizes and revenues
Firm_Size = data.pivot_table(columns="Size",index="Revenue_USD",values="Company Name",aggfunc=pd.Series.
Firm_Size = Firm_Size[['Revenue_USD','1 to 50 employees','51 to 200 employees','201 to 500 employees','5
Firm_Size = Firm_Size.reindex([11,2,9,4,7,10,5,0,1,6,8,3,12])
Firm_Size = Firm_Size.set_index('Revenue_USD').replace(np.nan,0)

# Create a table for heatmap of number of companies with different sizes and revenues in CA
Firm_Size_CA = data_CA.pivot_table(columns="Size",index="Revenue_USD",values="Company Name",aggfunc=pd.S
Firm_Size_CA = Firm_Size_CA[['Revenue_USD','1 to 50 employees','51 to 200 employees','201 to 500 employe
Firm_Size_CA = Firm_Size_CA.reindex([11,2,9,4,7,10,5,0,1,6,8,3,12])
Firm_Size_CA = Firm_Size_CA.set_index('Revenue_USD').replace(np.nan,0)

# Create table for heatmap of salaries by companies with different sizes and revenues
Firm_Size_Sal = data.pivot_table(columns="Size",index="Revenue_USD",values="Est_Salary",aggfunc=np.mean)
Firm_Size_Sal = Firm_Size_Sal[['Revenue_USD','1 to 50 employees','51 to 200 employees','201 to 500 emplo
Firm_Size_Sal = Firm_Size_Sal.reindex([11,2,9,4,7,10,5,0,1,6,8,3,12])
Firm_Size_Sal = Firm_Size_Sal.set_index('Revenue_USD').replace(np.nan,0)

# Create table for heatmap of salaries by companies with different sizes and revenues in CA
Firm_Size_CA_Sal = data_CA.pivot_table(columns="Size",index="Revenue_USD",values="Est_Salary",aggfunc=np
Firm_Size_CA_Sal = Firm_Size_CA_Sal[['Revenue_USD','1 to 50 employees','51 to 200 employees','201 to 500
Firm_Size_CA_Sal = Firm_Size_CA_Sal.reindex([11,2,9,4,7,10,5,0,1,6,8,3,12])
Firm_Size_CA_Sal = Firm_Size_CA_Sal.set_index('Revenue_USD').replace(np.nan,0)
```

In [165]:
```
f, axs = plt.subplots(nrows=2,ncols=2, sharey=True,sharex=True, figsize=(13,9))

fs = sns.heatmap(Firm_Size,annot=True,fmt='.0f',annot_kws={"size": 12},cmap="YlGnBu", ax=axs[0,0]).set(t
fsc = sns.heatmap(Firm_Size_CA,annot=True,fmt='.0f',annot_kws={"size": 12},cmap="YlGnBu", ax=axs[0,1]).s
fss = sns.heatmap(Firm_Size_Sal,annot=True,fmt='.0f',annot_kws={"size": 12},cmap="Oranges",ax=axs[1,0]).
fscs = sns.heatmap(Firm_Size_CA_Sal,annot=True,fmt='.0f',annot_kws={"size": 12},cmap="Oranges",ax=axs[1,

plt.setp([a.get_xticklabels() for a in axs[1,:]],rotation=45,ha='right')
plt.tight_layout()
plt.show()
```



- Big firms (10k+ employess and USD10B+ revenues) do the bulk of analyst hiring, but don't necessarily pay more

- Revenue "Unknown" firms have high demand amongst non-public fiannce firms. these firms pay similar or higher salaries than big firms

- medium-large firms (1k-5k employees and USD100M-USD500M revenues), small businesses (<50 employees and <USD5M revenues) and small-medium businesses (51-200 employees , unknown revenues) tend to pay more

- CA firms pay more

Who are those high-paying medium-large businesses in CA?

In [166]:
```
ca_sal_by_firm = data_CA.groupby('Company Name')[['Est_Salary']].mean().reset_index()
```

In [167]:
```
MLHighPay = data_CA[(data_CA['Revenue_USD']=='100-500 million')&(
    data_CA['Size']=='1001 to 5000 employees')]['Company Name'].value_counts().reset_index().rename(
    columns={'index':'Company Name','Company Name':'Hires'})
```

In [168]:

```
MLHighPay = MLHighPay.merge(ca_sal_by_firm, on='Company Name',how='left')
MLHighPay = MLHighPay.merge(data_CA[['Company Name','Rating','Headquarters','Type of ownership','Industr
MLHighPay = MLHighPay.drop_duplicates().reset_index(drop=True)
MLHighPay
```

Out[168]:

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
0	ICONMA	3	122.500000	3.6	Troy, MI	Company - Private	Staffing & Outsourcing	Business Services	20.0	Experis
1	Ascent	3	82.333333	4.6	Concord, CA	Company - Private	Staffing & Outsourcing	Business Services	20.0	NaN
2	The Ascent Services Group	2	60.500000	4.6	Concord, CA	Company - Private	Staffing & Outsourcing	Business Services	20.0	NaN
3	Stamps.com	1	79.000000	3.1	El Segundo, CA	Company - Public	Computer Hardware & Software	Information Technology	24.0	Pitney Bowes, US Postal Service, Envelope Mana...
4	Exact Sciences Corporation	1	120.000000	4.0	Madison, WI	Company - Public	Health Care Services & Hospitals	Health Care	25.0	NaN
5	Alteryx	1	150.000000	3.3	Irvine, CA	Company - Public	Enterprise Software & Network Solutions	Information Technology	23.0	NaN
6	U.S. Auto Parts Network, Inc.	1	54.000000	3.4	Carson, CA	Company - Public	Automotive Parts & Accessories Stores	Retail	25.0	AutoZone, eBay, Advance Auto Parts
7	Rose International	1	99.000000	4.5	Chesterfield, MO	Company - Private	Staffing & Outsourcing	Business Services	27.0	NaN
8	Sycuan Casino	1	92.000000	3.3	El Cajon, CA	Company - Private	Gambling	Arts, Entertainment & Recreation	37.0	Viejas Casino, Barona Casino, Pechanga Resort ...
9	Technosoft Corporation	1	98.000000	3.8	Southfield, MI	Company - Private	IT Services	Information Technology	24.0	NaN

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
10	eHealth	1	75.500000	3.7	Santa Clara, CA	Company - Public	Insurance Agencies & Brokerages	Insurance	23.0	InsWeb, Insure.com, Answer Financial
11	Net2Source	1	126.000000	3.2	Somerset, NJ	Company - Private	Staffing & Outsourcing	Business Services	13.0	NaN
12	US Tech Solutions, Inc	1	98.000000	3.7	Edison, NJ	Company - Private	Staffing & Outsourcing	Business Services	20.0	TEKsystems, Artech Information Systems, PDS Tech
13	Risk Management Solutions (RMS)	1	150.000000	3.9	Newark, CA	Company - Private	Enterprise Software & Network Solutions	Information Technology	31.0	AIR Worldwide, EQECAT, Verisk Analytics
14	Milestone Technologies Inc.	1	98.000000	3.2	Fremont, CA	Company - Private	IT Services	Information Technology	23.0	World Wide Technology, Astreya Partners, Taos
15	Iconma, L.L.C.	1	150.000000	3.6	Troy, MI	Company - Private	Staffing & Outsourcing	Business Services	20.0	Experis
16	ICONMA, LLC	1	75.500000	3.6	Troy, MI	Company - Private	Staffing & Outsourcing	Business Services	20.0	Experis
17	Incedo Inc	1	60.500000	3.4	Iselin, NJ	Company - Private	IT Services	Information Technology	8.0	Mu Sigma, ZS Associates, Fractal
18	Ajilon	1	54.000000	3.6	Jacksonville, FL	Company - Public	Staffing & Outsourcing	Business Services	26.0	NaN

In [169]:
```
MLHighPay.describe(include='all')
```

Out[169]:

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
count	19	19.000000	19.000000	19.000000	19	19	19	19	19.000000	11
unique	19	NaN	NaN	NaN	16	2	8	6	NaN	9
top	Rose International	NaN	NaN	NaN	Troy, MI	Company - Private	Staffing & Outsourcing	Business Services	NaN	Experis
freq	1	NaN	NaN	NaN	3	13	9	9	NaN	3
mean	NaN	1.263158	97.096491	3.689474	NaN	NaN	NaN	NaN	22.578947	NaN
std	NaN	0.653376	31.889727	0.459341	NaN	NaN	NaN	NaN	6.103877	NaN
min	NaN	1.000000	54.000000	3.100000	NaN	NaN	NaN	NaN	8.000000	NaN
25%	NaN	1.000000	75.500000	3.350000	NaN	NaN	NaN	NaN	20.000000	NaN
50%	NaN	1.000000	98.000000	3.600000	NaN	NaN	NaN	NaN	23.000000	NaN
75%	NaN	1.000000	121.250000	3.850000	NaN	NaN	NaN	NaN	25.000000	NaN
max	NaN	3.000000	150.000000	4.600000	NaN	NaN	NaN	NaN	37.000000	NaN

characteristics of these high-paying medium-large companies in CA ?

- most are private firms (1k-5k employees & USD100M-500M revenues)
- 50% of these are staffing firms or in outsourcing business
- avg hires 1.3; avg rating 3.7 (ttl avg 3.1); avg company age 22.6 (ttl avg 40)

Who are those high-paying small businesses in CA ?

In [170]:
```
smallHighPay = data_CA[((data_CA['Revenue_USD']=='<1 million')|(
    data_CA['Revenue_USD']=='1-5 million'))&(
    data_CA['Size']=='1 to 50 employees')]['Company Name'].value_counts().reset_index().rename(
    columns={'index':'Company Name','Company Name':'Hires'})
```

In [171]:
```
smallHighPay = smallHighPay.merge(ca_sal_by_firm, on='Company Name',how='left')
smallHighPay = smallHighPay.merge(data_CA[['Company Name','Rating','Headquarters','Type of ownership','I
smallHighPay = smallHighPay.drop_duplicates().reset_index(drop=True)
smallHighPay
```

Out[171]:

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
0	Lorven Technologies Inc	7	93.000000	4.0	Plainsboro, NJ	Company - Private	Accounting	Accounting & Legal	NaN	NaN
1	Kaygen Inc.	3	103.833333	3.9	Irvine, CA	Company - Private	Consulting	Business Services	NaN	NaN
2	Web Shop Manager	2	92.000000	4.2	San Diego, CA	Company - Private	Computer Hardware & Software	Information Technology	20.0	NaN
3	Introlligent Inc.	1	72.000000	3.7	Elk Grove, CA	Company - Private	Advertising & Marketing	Business Services	NaN	NaN
4	DT Professional Services	1	122.500000	NaN	Canoga Park, CA	Company - Public	NaN	NaN	7.0	NaN
5	Georgia IT Inc.	1	73.000000	5.0	Alpharetta, GA	Company - Private	NaN	NaN	NaN	NaN
6	HITRECORD	1	79.000000	3.5	Van Nuys, CA	Company - Private	NaN	NaN	NaN	NaN
7	Anzu Global	1	75.500000	4.8	Acton, MA	Company - Private	Consulting	Business Services	14.0	NaN
8	TCOE	1	64.000000	3.7	Springville, CA	School / School District	Preschool & Child Care	Education	NaN	NaN
9	Prime MSO, LLC.	1	54.000000	4.0	Dayton, OH	Company - Private	Health Care Services & Hospitals	Health Care	NaN	NaN
10	EMINENT, INC.	1	54.000000	3.4	Williamsville, NY	Company - Private	IT Services	Information Technology	NaN	NaN
11	Conflux Systems Inc.	1	99.000000	4.5	Alpharetta, GA	Company - Private	Accounting	Accounting & Legal	NaN	NaN
12	Apollo Medical Holdings, Inc.	1	40.000000	3.4	Sandy, UT	Company - Private	NaN	NaN	NaN	NaN

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
13	Two95 International Inc.	1	92.500000	4.0	Cherry Hill, NJ	Company - Private	Staffing & Outsourcing	Business Services	NaN	NaN
14	Marin City Health and Wellness Center	1	126.000000	4.5	Marin City, CA	Nonprofit Organization	Health Care Services & Hospitals	Health Care	13.0	NaN
15	SGA Inc.	1	138.500000	NaN	Bethesda, MD	Company - Private	Architectural & Engineering Services	Business Services	24.0	NaN
16	Centrillion	1	75.500000	2.2	Palo Alto, CA	Company - Private	Biotech & Pharmaceuticals	Biotech & Pharmaceuticals	11.0	NaN
17	Concept Software & Services Inc	1	60.500000	5.0	Alpharetta, GA	Company - Private	Consulting	Business Services	22.0	NaN
18	Softova Inc	1	126.000000	5.0	Piscataway, NJ	Company - Private	IT Services	Information Technology	NaN	NaN
19	United IT Solutions	1	99.000000	3.8	Irving, TX	Company - Private	Consulting	Business Services	10.0	NaN
20	Frontend Arts	1	120.000000	4.5	Irving, TX	Company - Private	Enterprise Software & Network Solutions	Information Technology	7.0	NaN
21	Optima Global Solutions	1	89.500000	3.9	Lawrenceville, NJ	Company - Private	IT Services	Information Technology	19.0	NaN
22	Focal Systems	1	99.000000	3.8	Burlingame, CA	Company - Private	Computer Hardware & Software	Information Technology	5.0	NaN
23	Softcom Systems	1	98.000000	4.4	Princeton, NJ	Company - Private	IT Services	Information Technology	NaN	NaN
24	Redolent, Inc	1	92.500000	3.7	Newark, CA	Company - Private	Health, Beauty, & Fitness	Consumer Services	NaN	NaN
25	Wellth Inc.	1	79.000000	5.0	New York, NY	Company - Private	Enterprise Software & Network Solutions	Information Technology	6.0	NaN

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
26	Priceonomics	1	138.500000	5.0	San Francisco, CA	Company - Private	Internet	Information Technology	NaN	NaN
27	PlushCare	1	138.500000	3.5	San Francisco, CA	Company - Private	Health Care Services & Hospitals	Health Care	NaN	NaN
28	TechNet Inc.	1	120.000000	5.0	Alpharetta, GA	Company - Private	Staffing & Outsourcing	Business Services	NaN	NaN

In [172]:

```
smallHighPay.describe(include='all')
```

Out[172]:

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
count	29	29.000000	29.000000	27.000000	29	29	25	25	12.000000	0
unique	29	NaN	NaN	NaN	24	4	13	7	NaN	0
top	Web Shop Manager	NaN	NaN	NaN	Alpharetta, GA	Company - Private	Consulting	Information Technology	NaN	NaN
freq	1	NaN	NaN	NaN	4	26	4	9	NaN	NaN
mean	NaN	1.310345	93.614943	4.125926	NaN	NaN	NaN	NaN	13.166667	NaN
std	NaN	1.168132	27.100273	0.679136	NaN	NaN	NaN	NaN	6.644661	NaN
min	NaN	1.000000	40.000000	2.200000	NaN	NaN	NaN	NaN	5.000000	NaN
25%	NaN	1.000000	75.500000	3.700000	NaN	NaN	NaN	NaN	7.000000	NaN
50%	NaN	1.000000	92.500000	4.000000	NaN	NaN	NaN	NaN	12.000000	NaN
75%	NaN	1.000000	120.000000	4.650000	NaN	NaN	NaN	NaN	19.250000	NaN
max	NaN	7.000000	138.500000	5.000000	NaN	NaN	NaN	NaN	24.000000	NaN

characteristics of these high-paying small business in CA ?

- private companies (<50 employees and <USD5M revenues)

- IT and related industrys, industry and sector is scattered

- avg hire 1.3 , avg rating 4.1 (ttl avg 3.1), avg company age 13.17 (ttl avg 40)

Who are those high-paying small-medium businesses in CA ?

In [173]:
```
SMHighPay = data_CA[(data_CA['Revenue_USD']=='Unknown')&(
    data_CA['Size']=='51 to 200 employees')]['Company Name'].value_counts().reset_index().rename(
    columns={'index':'Company Name','Company Name':'Hires'})
```

In [174]:

```
SMHighPay = SMHighPay.merge(ca_sal_by_firm, on='Company Name',how='left')
SMHighPay = SMHighPay.merge(data_CA[['Company Name','Rating','Headquarters','Type of ownership','Industr
SMHighPay = SMHighPay.drop_duplicates().reset_index(drop=True)
SMHighPay
```

Out[174]:

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
0	Armada Group, Inc.	2	85.0	4.4	Santa Cruz, CA	Company - Private	IT Services	Information Technology	25.0	TEKsystems, Akraya, Intelliswift
1	Parker Institute for Cancer Immunotherapy	2	76.5	NaN	San Francisco, CA	Nonprofit Organization	Health Fundraising Organizations	Non-Profit	NaN	NaN
2	Adwait Algorithm	2	109.0	4.4	Houston, TX	Company - Private	IT Services	Information Technology	5.0	NaN
3	Potomac Management	2	95.5	3.5	Hagerstown, MD	Nonprofit Organization	NaN	NaN	NaN	NaN
4	PlayQ	2	76.0	4.7	Santa Monica, CA	Company - Private	Video Games	Media	13.0	NaN
5	Quinn Group	1	122.5	5.0	Taipei, Taiwan	Company - Private	NaN	NaN	NaN	NaN
6	LaunchDarkly	1	80.5	5.0	Oakland, CA	Company - Private	Enterprise Software & Network Solutions	Information Technology	6.0	NaN
7	Method360	1	98.0	4.7	San Francisco, CA	Company - Private	IT Services	Information Technology	20.0	Optimal Solutions Integration, Capgemini
8	NRC INC	1	122.5	4.0	Boca Raton, FL	Company - Private	NaN	NaN	NaN	NaN
9	Sayva Solutions	1	99.0	4.8	La Jolla, CA	Company - Private	Staffing & Outsourcing	Business Services	6.0	NaN
10	TutorMe	1	80.0	4.6	Los Angeles, CA	Subsidiary or Business Segment	Colleges & Universities	Education	5.0	Chegg, Tutor.com, Smarthinking
11	Deliverr Inc	1	80.5	4.9	San Francisco, CA	Company - Private	Logistics & Supply Chain	Transportation & Logistics	3.0	NaN

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
12	The Armada Group	1	66.0	4.4	Santa Cruz, CA	Company - Private	IT Services	Information Technology	25.0	TEKsystems, Akraya, Intelliswift
13	LiveGlam	1	53.5	4.1	Los Angeles, CA	Company - Private	Health, Beauty, & Fitness	Consumer Services	4.0	NaN
14	Trifacta	1	138.5	3.6	San Francisco, CA	Company - Private	Computer Hardware & Software	Information Technology	8.0	Paxata, Datameer, Informatica
15	Applicantz	1	99.0	NaN	Houston, TX	Company - Public	NaN	NaN	NaN	NaN
16	PETADATA	1	98.0	NaN	Fremont, CA	Company - Private	NaN	NaN	NaN	NaN
17	LeadStack	1	126.0	4.1	San Francisco, CA	Company - Private	IT Services	Information Technology	4.0	NaN
18	Lean Data	1	98.0	4.0	Hyderabad, India	Company - Private	NaN	NaN	NaN	NaN
19	Moveworks	1	150.0	5.0	Mountain View, CA	Company - Private	Enterprise Software & Network Solutions	Information Technology	4.0	NaN
20	Angaza	1	80.5	4.6	San Francisco, CA	Company - Private	Enterprise Software & Network Solutions	Information Technology	10.0	NaN
21	Mobilityware	1	80.0	4.5	Irvine, CA	Company - Private	Video Games	Media	30.0	NaN
22	Scale AI	1	126.0	3.2	San Francisco, CA	Company - Private	Enterprise Software & Network Solutions	Information Technology	4.0	NaN
23	Cue	1	99.0	4.2	San Diego, CA	Company - Private	Biotech & Pharmaceuticals	Biotech & Pharmaceuticals	10.0	NaN
24	Credible	1	138.5	4.3	San Francisco, CA	Company - Public	Lending	Finance	8.0	NaN
25	Housecall Pro	1	92.0	4.6	San Diego, CA	Company - Private	Computer Hardware & Software	Information Technology	7.0	NaN

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
26	IT Avalon	1	99.0	NaN	Brentwood, CA	Unknown	NaN	NaN	NaN	NaN
27	Signal Sciences	1	79.0	4.3	Culver City, CA	Company - Private	Enterprise Software & Network Solutions	Information Technology	6.0	NaN
28	Vida Health	1	99.0	3.3	San Francisco, CA	Company - Private	Health Care Services & Hospitals	Health Care	6.0	NaN
29	Vinsari LLC	1	126.0	2.5	Irving, TX	Other Organization	NaN	NaN	NaN	NaN
30	Gossamer Bio	1	92.0	NaN	San Diego, CA	Company - Public	NaN	NaN	NaN	NaN
31	Life360	1	80.5	3.9	San Francisco, CA	Company - Public	Internet	Information Technology	12.0	NaN
32	Century Group (CA)	1	80.0	4.5	El Segundo, CA	Company - Private	Staffing & Outsourcing	Business Services	31.0	NaN
33	Leo Tech, LLC	1	54.0	3.5	Singapore, Singapore	Company - Private	NaN	NaN	NaN	NaN
34	The Voleon Group	1	138.5	4.6	Berkeley, CA	Company - Private	Investment Banking & Asset Management	Finance	13.0	NaN
35	Tech Firefly	1	98.0	4.5	Santa Clara, CA	Company - Private	IT Services	Information Technology	4.0	NaN
36	Skiltrek	1	89.5	NaN	Jacksonville, FL	Company - Public	NaN	NaN	NaN	NaN
37	PeerStreet	1	79.0	4.7	El Segundo, CA	Company - Private	Real Estate	Real Estate	NaN	NaN
38	Epikso	1	60.5	3.8	Pleasant Hill, CA	Company - Private	Research & Development	Business Services	5.0	NaN
39	Chinese Community Health Plan	1	99.0	3.2	San Francisco, CA	Company - Private	Insurance Carriers	Insurance	NaN	NaN
40	Joomag, Inc.	1	150.0	3.9	Sunnyvale, CA	Company - Private	IT Services	Information Technology	11.0	NaN

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
41	LeadStack, Inc.	1	92.5	4.1	San Francisco, CA	Company - Private	IT Services	Information Technology	4.0	NaN
42	Center For Policing Equity	1	53.5	NaN	New York, NY	Nonprofit Organization	Colleges & Universities	Education	NaN	NaN
43	DISQO	1	73.0	4.7	Glendale, CA	Company - Private	Research & Development	Business Services	6.0	NaN
44	Applicantz, Inc.	1	138.5	NaN	Houston, TX	Company - Public	NaN	NaN	NaN	NaN
45	Cypress HCM	1	40.0	4.9	Walnut Creek, CA	Company - Private	Staffing & Outsourcing	Business Services	15.0	NaN
46	Allakos	1	72.0	NaN	Redwood City, CA	Company - Public	NaN	NaN	NaN	NaN
47	Epikso Inc	1	60.5	3.8	Pleasant Hill, CA	Company - Private	Research & Development	Business Services	5.0	NaN
48	Mindstrong	1	80.5	3.6	Mountain View, CA	Company - Private	IT Services	Information Technology	6.0	NaN
49	Perfect Day	1	99.0	4.4	Emeryville, CA	Company - Private	Biotech & Pharmaceuticals	Biotech & Pharmaceuticals	6.0	NaN

In [175]:
```
SMHighPay.describe(include='all')
```

Out[175]:

	Company Name	Hires	Est_Salary	Rating	Headquarters	Type of ownership	Industry	Sector	Years_Founded	Competitors
count	50	50.000000	50.000000	41.000000	50	50	37	37	33.000000	5
unique	50	NaN	NaN	NaN	30	6	17	12	NaN	4
top	IT Avalon	NaN	NaN	NaN	San Francisco, CA	Company - Private	IT Services	Information Technology	NaN	TEKsystems, Akraya, Intelliswift
freq	1	NaN	NaN	NaN	12	37	9	17	NaN	2
mean	NaN	1.100000	94.070000	4.214634	NaN	NaN	NaN	NaN	9.909091	NaN
std	NaN	0.303046	26.262608	0.577737	NaN	NaN	NaN	NaN	7.771597	NaN
min	NaN	1.000000	40.000000	2.500000	NaN	NaN	NaN	NaN	3.000000	NaN
25%	NaN	1.000000	79.250000	3.900000	NaN	NaN	NaN	NaN	5.000000	NaN
50%	NaN	1.000000	92.250000	4.400000	NaN	NaN	NaN	NaN	6.000000	NaN
75%	NaN	1.000000	99.000000	4.600000	NaN	NaN	NaN	NaN	12.000000	NaN
max	NaN	2.000000	150.000000	5.000000	NaN	NaN	NaN	NaN	31.000000	NaN

characteristics of these high-paying small business in CA ?

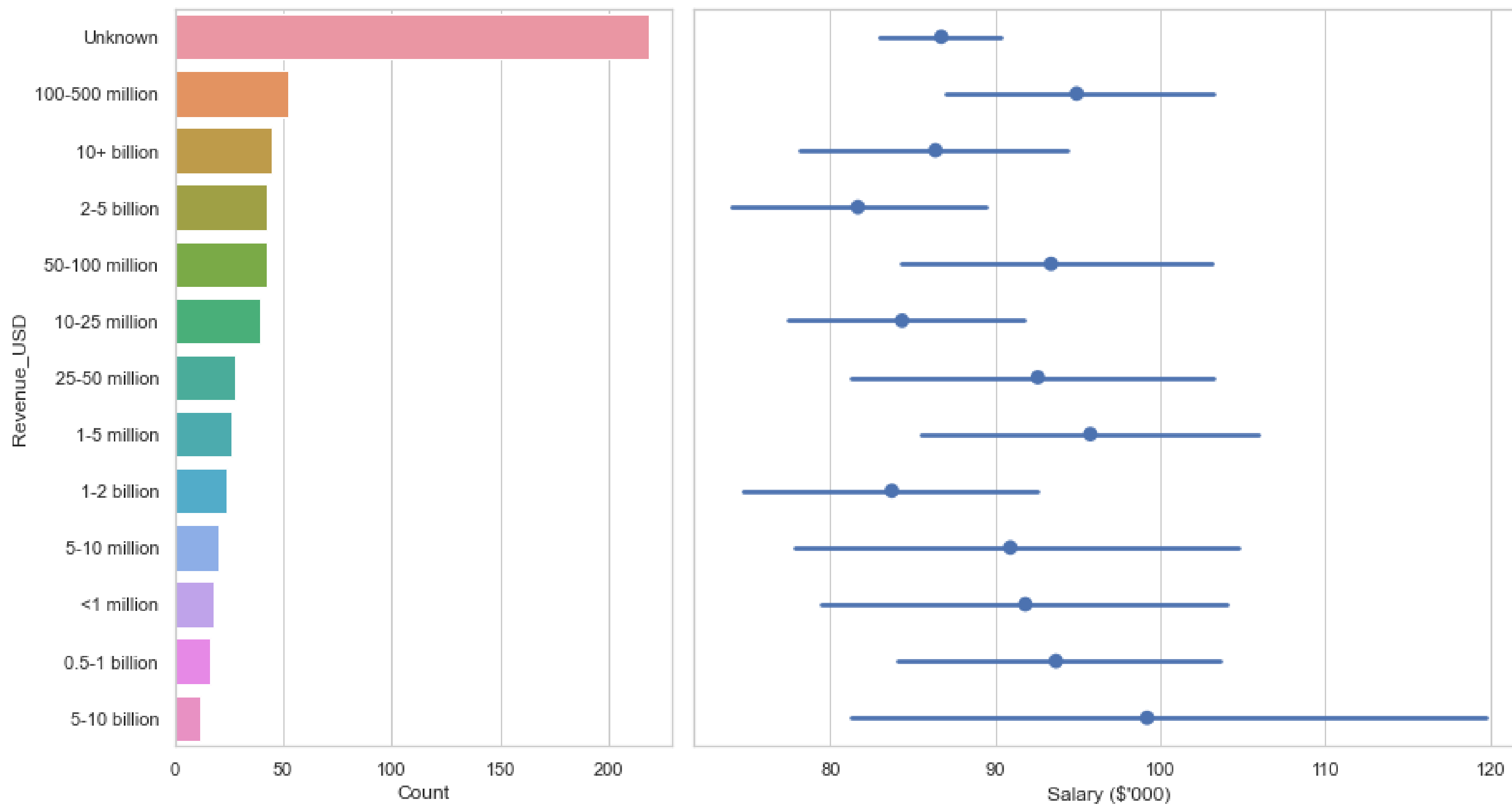
- private compaies (51-200 employees with unknown revenues)
- 50% are IT related
- avg hires 1.1 ; avg rating 4.2 (hiugher than ttl avg 3.1); avg compamy age 9.9 (ttl avg 40)

CA - Hires and Salary Estimates by Revenues

CA - Hires and Salary Estimates by Revenues

In [176]:
```
RevCountCA = data_CA.groupby('Revenue_USD')[['Job Title']].count().reset_index().rename(columns={'Job Ti
    'Count', ascending=False).reset_index(drop=True)
RevCountCA = RevCountCA.merge(data_CA, on='Revenue_USD',how='left')
```

In [177]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Count',y='Revenue_USD',data=RevCountCA,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Revenue_USD',data=RevCountCA, join=False,ax=ax_point).set(ylabel="",xlab

plt.tight_layout()
```

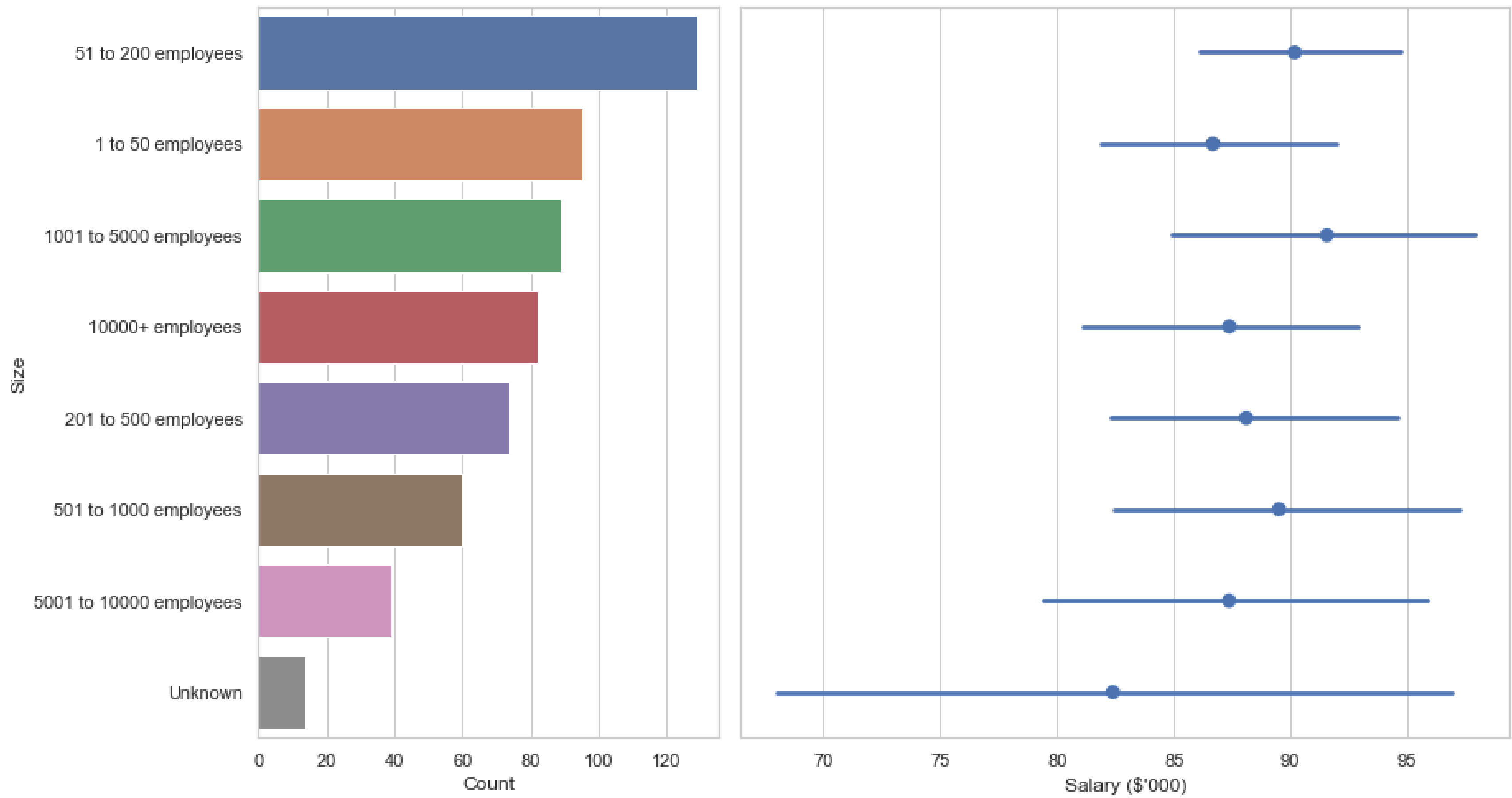


- in CA, majority of the analyst hirings are with firms with unknown revenues

CA - Hires and Salary Estimates by Sizes

In [179]:
```
SizeCountCA = data_CA.groupby('Size')[['Job Title']].count().reset_index().rename(columns={'Job Title':'
    'Count', ascending=False).reset_index(drop=True)
SizeCountCA = SizeCountCA.merge(data_CA, on='Size',how='left')
```

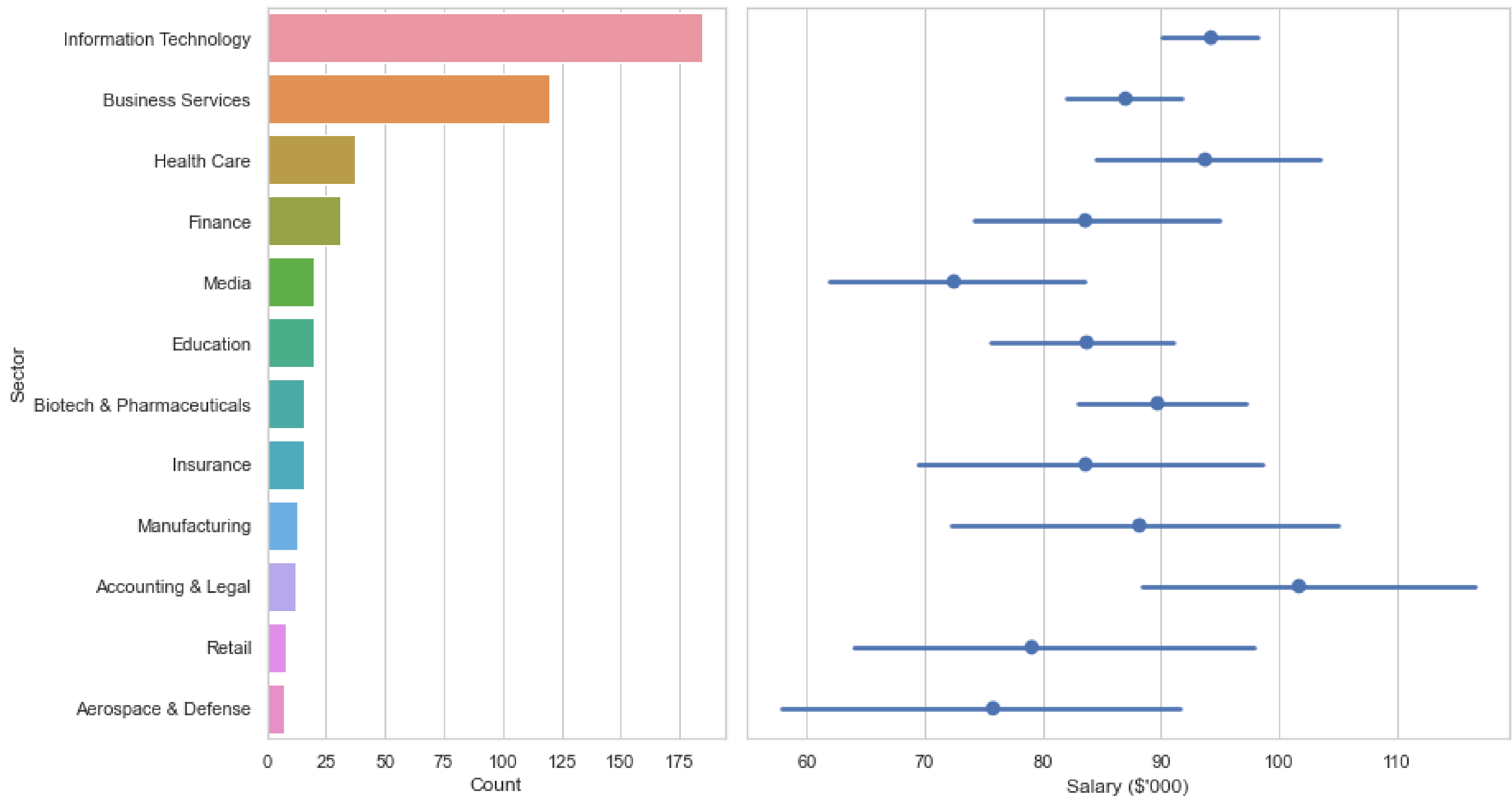
In [180]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Count',y='Size',data=SizeCountCA,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Size',data=SizeCountCA, join=False,ax=ax_point).set(ylabel="",xlabel="Sa

plt.tight_layout()
```



CA - Hires and Salary Estimates by Sectors

In [181]:
```
SecCountCA = data_CA.groupby('Sector')[['Job Title']].count().reset_index().rename(columns={'Job Title':
    'Count', ascending=False).head(12).reset_index(drop=True)
SecCountCA = SecCountCA.merge(data_CA, on='Sector',how='left')
```

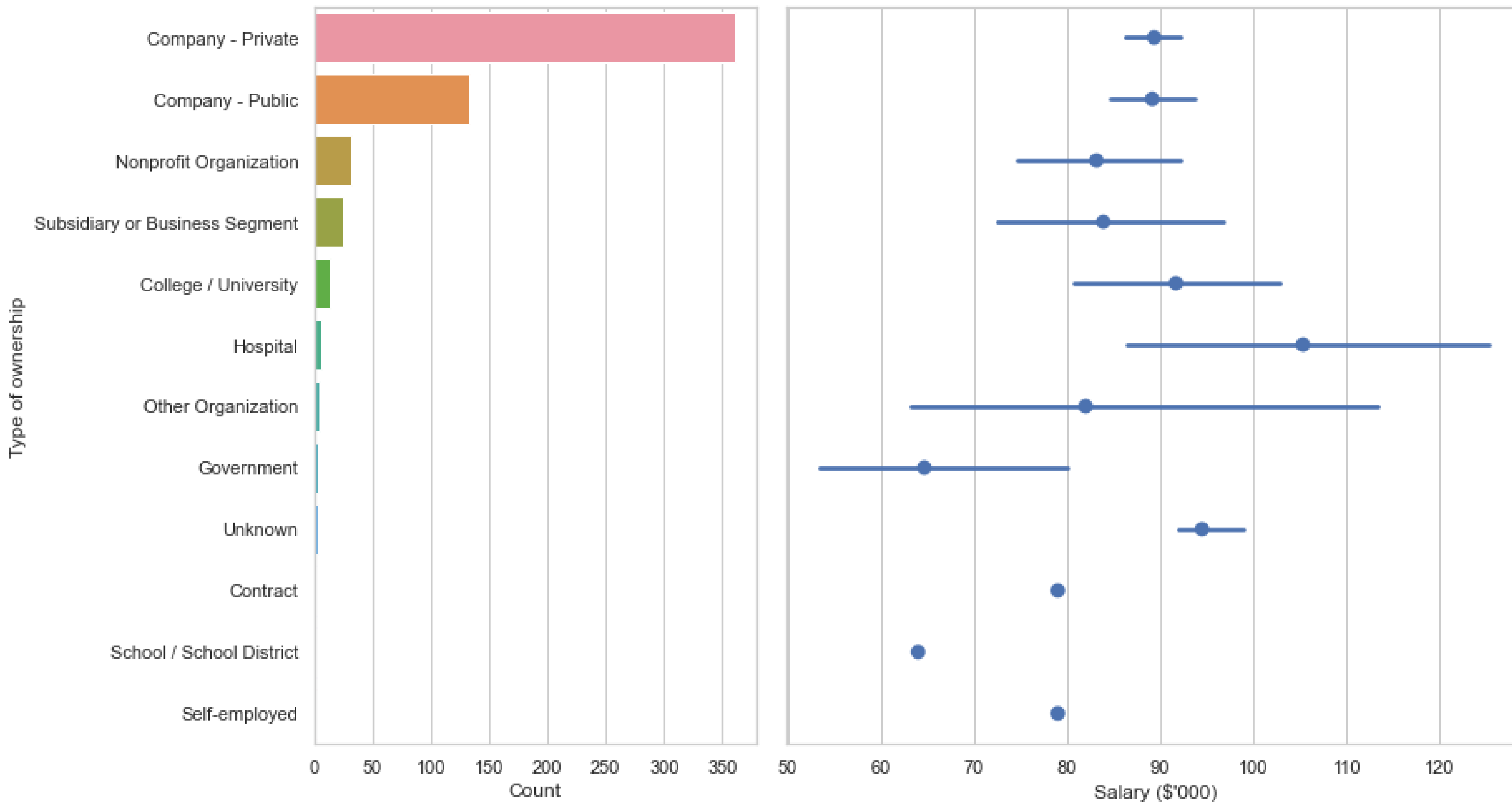
In [182]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Count',y='Sector',data=SecCountCA,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Sector', join=False,data=SecCountCA,ax=ax_point).set(ylabel="",xlabel="S

plt.tight_layout()
```



CA - Hires and Salary Estimates by Types of Ownership

In [183]:
```
OwnCountCA = data_CA.groupby('Type of ownership')[['Job Title']].count().reset_index().rename(columns={'
    'Count', ascending=False).reset_index(drop=True)
OwnCountCA = OwnCountCA.merge(data_CA, on='Type of ownership',how='left')
```

In [184]:
```
sns.set(style="whitegrid")
f, (ax_bar, ax_point) = plt.subplots(ncols=2, sharey=True, gridspec_kw= {"width_ratios":(0.6,1)},figsize
sns.barplot(x='Count',y='Type of ownership',data=OwnCountCA,ax=ax_bar)
sns.pointplot(x='Est_Salary',y='Type of ownership',data=OwnCountCA, join=False,ax=ax_point).set(ylabel='

plt.tight_layout()
```



In [ ]: