Final Report

December 8, 2022

1 UK Gender Pay Gap Analysis Final Report

Bea Igbokwe, Anusha Ramprasad, Nivedita Ravi IST 462/652 December 7, 2022

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

1.1 Data Cleaning

To start the analysis of the UK gender pay gap, we read the csv files for the years 2019 through 2021, omitting columns that would not be utilized within our analysis. We determined the columns pertaining to income and employer size for each company would be our focus for this analysis.

These columns were EmployerName, DiffMeanHourlyPercent, DiffMedianHourlyPercent, DiffMeanBonusPercent, DiffMedianBonusPercent, MaleBonusPercent, FemaleBonusPercent, MaleLowerQuartile, FemaleLowerQuartile, MaleLowerMiddleQuartile, FemaleLowerMiddleQuartile, MaleUpperMiddleQuartile, FemaleUpperMiddleQuartile, MaleTopQuartile, FemaleTopQuartile, and EmployerSize– leaving us with 16 columns remaining from our original 27. Columns 2 through 4 focus on the difference of pay between men and women, measuring the mean/median of hourly/bonus pay, with a negative value in the dataset implying there are higher percentage of women with the higher pay. Columns 5 through 15 divide the hourly pay of employees into quartiles, then further divides them into male and female– these two columns for each division adding up to 100. For the last column, each row had a value out of a list to provide data on the employer size: "Less than 250", "250 to 499", "500 to 999", "1000 to 4999","5000 to 19,999", "20,000 or more", "Not Provided".

By observing the info for each dataset, we could conclude the size of our datasets and which columns contained null values. For the years 2020 and 2021, there were over 10,000 rows with 2019 having significantly less rows at a bit over 6,900 rows.

[2]:
```
gpg_2021 = pd.read_csv("https://gender-pay-gap.service.gov.uk/viewing/
↪download-data/2021")
```

[3]:
```
gpg_21 = gpg_2021.drop(["Address", "PostCode", "CompanyNumber", "SicCodes",␣
↪"ResponsiblePerson", "CompanyLinkToGPGInfo", "CurrentName",␣
↪"DueDate","EmployerId", "DateSubmitted", "SubmittedAfterTheDeadline" ], axis␣
↪= 1)
```

[4]:
```
gpg_21.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10492 entries, 0 to 10491
Data columns (total 16 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   EmployerName                10492 non-null  object
 1   DiffMeanHourlyPercent       10492 non-null  float64
 2   DiffMedianHourlyPercent     10492 non-null  float64
 3   DiffMeanBonusPercent        7685 non-null   float64
 4   DiffMedianBonusPercent      7685 non-null   float64
 5   MaleBonusPercent            10492 non-null  float64
 6   FemaleBonusPercent          10492 non-null  float64
 7   MaleLowerQuartile           10295 non-null  float64
 8   FemaleLowerQuartile         10295 non-null  float64
 9   MaleLowerMiddleQuartile     10295 non-null  float64
 10  FemaleLowerMiddleQuartile   10295 non-null  float64
 11  MaleUpperMiddleQuartile     10295 non-null  float64
 12  FemaleUpperMiddleQuartile   10295 non-null  float64
 13  MaleTopQuartile             10295 non-null  float64
 14  FemaleTopQuartile           10295 non-null  float64
 15  EmployerSize                10492 non-null  object
dtypes: float64(14), object(2)
memory usage: 1.3+ MB
```

[5]:
```
gpg_20 = pd.read_csv("https://gender-pay-gap.service.gov.uk/viewing/
↪download-data/2020",
                     usecols=['DiffMeanBonusPercent',
 'DiffMeanHourlyPercent',
 'DiffMedianBonusPercent',
 'DiffMedianHourlyPercent',
 'EmployerName',
 'EmployerSize',
 'FemaleBonusPercent',
 'FemaleLowerMiddleQuartile',
 'FemaleLowerQuartile',
 'FemaleTopQuartile',
 'FemaleUpperMiddleQuartile',
 'MaleBonusPercent',
 'MaleLowerMiddleQuartile',
 'MaleLowerQuartile',
```

```
'MaleTopQuartile',
 'MaleUpperMiddleQuartile'])
```

[6]:
```
gpg_20.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10532 entries, 0 to 10531
Data columns (total 16 columns):
 #   Column                    Non-Null Count  Dtype
---  ------                    --------------  -----
 0   EmployerName              10532 non-null  object
 1   DiffMeanHourlyPercent     10532 non-null  float64
 2   DiffMedianHourlyPercent   10532 non-null  float64
 3   DiffMeanBonusPercent      7894 non-null   float64
 4   DiffMedianBonusPercent    7894 non-null   float64
 5   MaleBonusPercent          10532 non-null  float64
 6   FemaleBonusPercent        10532 non-null  float64
 7   MaleLowerQuartile         10332 non-null  float64
 8   FemaleLowerQuartile       10332 non-null  float64
 9   MaleLowerMiddleQuartile   10332 non-null  float64
 10  FemaleLowerMiddleQuartile 10332 non-null  float64
 11  MaleUpperMiddleQuartile   10332 non-null  float64
 12  FemaleUpperMiddleQuartile 10332 non-null  float64
 13  MaleTopQuartile           10332 non-null  float64
 14  FemaleTopQuartile         10332 non-null  float64
 15  EmployerSize              10532 non-null  object
dtypes: float64(14), object(2)
memory usage: 1.3+ MB
```

[7]:
```
gpg_19 = pd.read_csv("https://gender-pay-gap.service.gov.uk/viewing/
 ↪download-data/2019",
                     usecols=['DiffMeanBonusPercent',
 'DiffMeanHourlyPercent',
 'DiffMedianBonusPercent',
 'DiffMedianHourlyPercent',
 'EmployerName',
 'EmployerSize',
 'FemaleBonusPercent',
 'FemaleLowerMiddleQuartile',
 'FemaleLowerQuartile',
 'FemaleTopQuartile',
 'FemaleUpperMiddleQuartile',
 'MaleBonusPercent',
 'MaleLowerMiddleQuartile',
 'MaleLowerQuartile',
 'MaleTopQuartile',
 'MaleUpperMiddleQuartile'])
```

```
[8]: gpg_19.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6921 entries, 0 to 6920
Data columns (total 16 columns):
 #   Column                      Non-Null Count  Dtype
---  ------                      --------------  -----
 0   EmployerName                6921 non-null   object
 1   DiffMeanHourlyPercent       6921 non-null   float64
 2   DiffMedianHourlyPercent     6921 non-null   float64
 3   DiffMeanBonusPercent        5205 non-null   float64
 4   DiffMedianBonusPercent      5203 non-null   float64
 5   MaleBonusPercent            6921 non-null   float64
 6   FemaleBonusPercent          6921 non-null   float64
 7   MaleLowerQuartile           6921 non-null   float64
 8   FemaleLowerQuartile         6921 non-null   float64
 9   MaleLowerMiddleQuartile     6921 non-null   float64
 10  FemaleLowerMiddleQuartile   6921 non-null   float64
 11  MaleUpperMiddleQuartile     6921 non-null   float64
 12  FemaleUpperMiddleQuartile   6921 non-null   float64
 13  MaleTopQuartile             6921 non-null   float64
 14  FemaleTopQuartile           6921 non-null   float64
 15  EmployerSize                6921 non-null   object
dtypes: float64(14), object(2)
memory usage: 865.2+ KB
```

1.2 Data Exploration of Employer Size

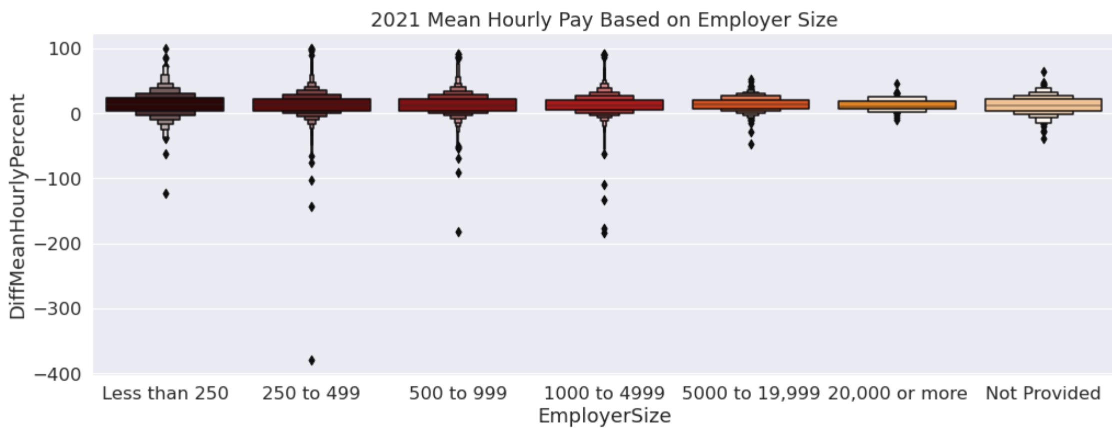
Next, we wanted to observe pay disparity based on the employer size. Focusing on the datasets for the years 2019 and 2021, we created visualizations to analyze how employer size changes the average hourly pay for men and women. To create comprehensive visualizations, we decided to use boxen plots that shows the distribution of each employer size value and order it from smallest to largest, with the last value being "Not Provided". To use this variable to analyze pay disparity, we decided to focus on the difference in the average hourly pay, which provides a percentage for each employer indicating a numeric value that is negative or positive.

```
[9]: gpg_21['EmployerSize'].unique()
```

```
[9]: array(['1000 to 4999', '250 to 499', 'Less than 250', '5000 to 19,999',
            '500 to 999', 'Not Provided', '20,000 or more'], dtype=object)
```

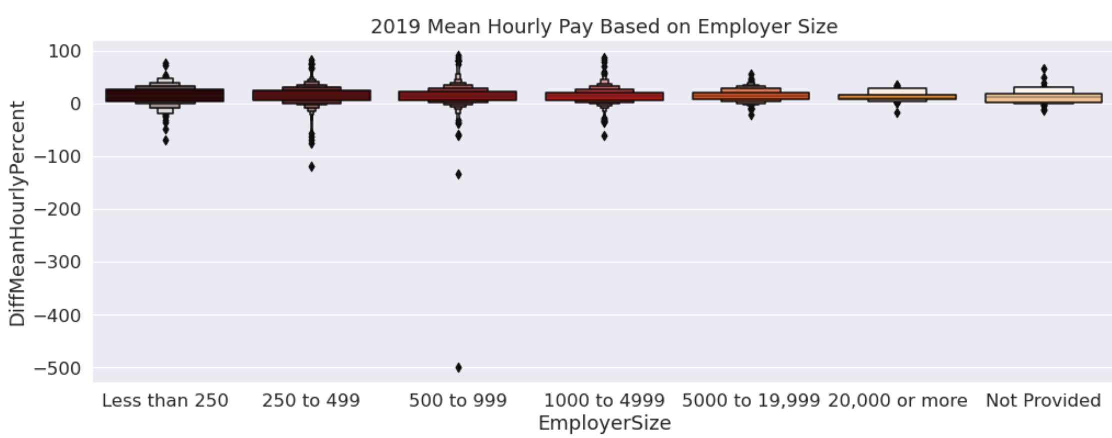
```
[10]: sns.set(rc={'figure.figsize':(16.75,5.75)}, font_scale = 1.5)
sns.boxenplot(data=gpg_21,
            x = "EmployerSize",
            y = "DiffMeanHourlyPercent",
            order = ["Less than 250", "250 to 499", "500 to 999", "1000 to␣
 ↪4999",
                    "5000 to 19,999", "20,000 or more", "Not Provided"],
```

```
            palette = "gist_heat"
             ).set(title='2021 Mean Hourly Pay Based on Employer Size')
plt.savefig('EmplySize21.pdf')
```



From looking at the visualization, it appears there are extreme outliers for women, as the negative values represent bias for women. These outliers appear to be more apparent for employer sizes less than 5000. Despite the outliers representing women, the boxen plots show the average mean hourly pay favors men as the median line is above 0.

[11]:
```
sns.set(rc={'figure.figsize':(16.75,5.75)}, font_scale = 1.5)
sns.boxenplot(data=gpg_19,
            x = "EmployerSize",
            y = "DiffMeanHourlyPercent",
            order = ["Less than 250", "250 to 499", "500 to 999", "1000 to␣
↪4999",
                    "5000 to 19,999", "20,000 or more", "Not Provided"],
            palette = "gist_heat"
             ).set(title='2019 Mean Hourly Pay Based on Employer Size')
plt.savefig('EmplySize19.pdf')
```



Similarly to the boxen plot for 2021, there are extreme outliers for the women who have an hourly pay largerly greater than the average. For this year, however, there is less of a disparity with the gap appearing to be smaller between men and women. Some factors for this could be related to the amount of data received for this year compared to 2021 and prehaps an increase in diversity of job roles in 2021.

1.3 Data Exploration of Employer

To explore gender bias amongst employers, we decided to focus on the extreme ends of our datasets. Looking at median hourly pay, we extracted the 5 employers who had the highest median hourly pay for men and the 5 employers who had the highest median hourly pay for women, then we created two small dataframes that can be used for graphs. For this data exploration we looked at the year 2021 to gain some insight before doing further analysis.

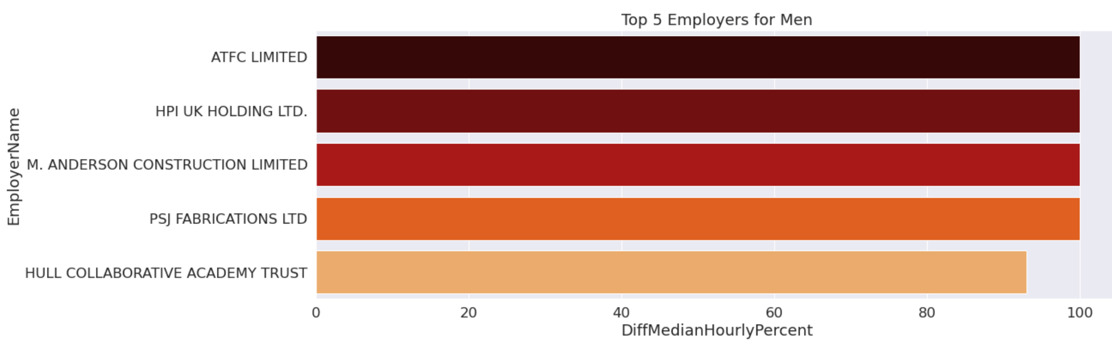
[12]:
```python
top5_21 = gpg_21.nlargest(5, 'DiffMedianHourlyPercent')
top5_21
```

[12]:
```
                         EmployerName  DiffMeanHourlyPercent  \
689                      ATFC LIMITED                    0.0
4343             HPI UK HOLDING LTD.                   100.0
5517  M. ANDERSON CONSTRUCTION LIMITED                 100.0
7197            PSJ FABRICATIONS LTD                   100.0
4369  HULL COLLABORATIVE ACADEMY TRUST                  45.0

      DiffMedianHourlyPercent  DiffMeanBonusPercent  DiffMedianBonusPercent  \
689                     100.0                   NaN                     NaN
4343                    100.0                   2.0                    59.0
5517                    100.0                 100.0                   100.0
7197                    100.0                 100.0                   100.0
4369                     93.0                   NaN                     NaN

      MaleBonusPercent  FemaleBonusPercent  MaleLowerQuartile  \
689                0.0                 0.0                NaN
4343              11.0                 4.0              100.0
5517              14.0                 0.0              100.0
7197               3.7                 0.0              100.0
4369               0.0                 0.0                3.0

      FemaleLowerQuartile  MaleLowerMiddleQuartile  FemaleLowerMiddleQuartile  \
689                   NaN                      NaN                        NaN
4343                  0.0                    100.0                        0.0
5517                  0.0                    100.0                        0.0
7197                  0.0                    100.0                        0.0
4369                 97.0                      3.0                       97.0
```

```
      MaleUpperMiddleQuartile  FemaleUpperMiddleQuartile  MaleTopQuartile  \
689                       NaN                        NaN              NaN
4343                    100.0                        0.0            100.0
5517                    100.0                        0.0            100.0
7197                    100.0                        0.0            100.0
4369                     17.0                       83.0             17.0

      FemaleTopQuartile   EmployerSize
689                 NaN     250 to 499
4343                0.0     250 to 499
5517                0.0     250 to 499
7197                0.0  Less than 250
4369               83.0   Not Provided
```

[13]:
```
sns.barplot(data=top5_21,
            y = "EmployerName",
            x = 'DiffMedianHourlyPercent',
            orient = "h",
           palette = "gist_heat"
           ).set(title="Top 5 Employers for Men")
```

[13]:
```
[Text(0.5, 1.0, 'Top 5 Employers for Men')]
```



By observing this bar plot, it is concluded there is a gender bias amongst some employers that is most likely affected by the industry. From this vizualization, we can see several construction companies that have 100% median hourly pay for men, implying there really isn't any women in this company to begin with.

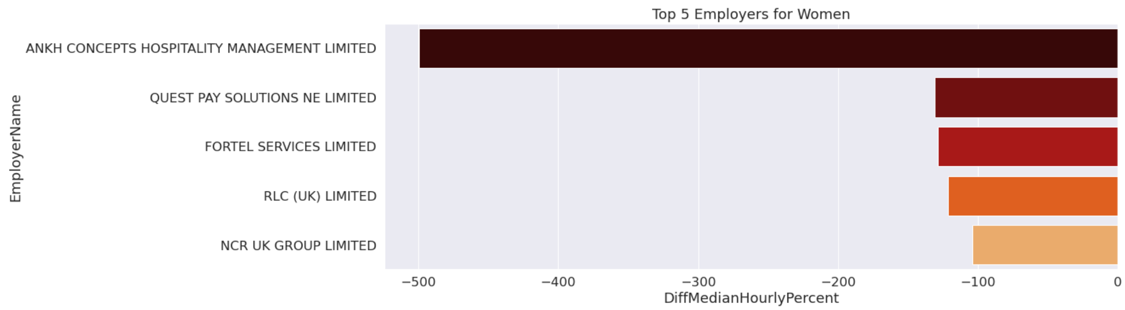
[14]:
```
last5_21 = gpg_21.nsmallest(5, 'DiffMedianHourlyPercent')
last5_21
```

[14]:
```
                                     EmployerName  DiffMeanHourlyPercent  \
472   ANKH CONCEPTS HOSPITALITY MANAGEMENT LIMITED                 -379.6
7256                 QUEST PAY SOLUTIONS NE LIMITED                  -90.0
3449                          FORTEL SERVICES LIMITED                 -184.2
```

```
7522                          RLC (UK) LIMITED                    -40.9
6180                      NCR UK GROUP LIMITED                    -53.0

      DiffMedianHourlyPercent  DiffMeanBonusPercent  DiffMedianBonusPercent  \
472                    -499.5                   NaN                     NaN
7256                   -131.0                   NaN                     NaN
3449                   -128.8                  63.5                    -6.7
7522                   -121.5                  30.9                     0.0
6180                   -104.0                -105.0                  -326.0

      MaleBonusPercent  FemaleBonusPercent  MaleLowerQuartile  \
472                0.0                 0.0                NaN
7256               0.0                 0.0               95.0
3449              12.9                30.4               93.4
7522              15.5                 6.1                NaN
6180              97.0                95.0               97.0

      FemaleLowerQuartile  MaleLowerMiddleQuartile  FemaleLowerMiddleQuartile  \
472                   NaN                      NaN                        NaN
7256                  5.0                     92.0                        8.0
3449                  6.6                     99.0                        1.0
7522                  NaN                      NaN                        NaN
6180                  3.0                     97.0                        3.0

      MaleUpperMiddleQuartile  FemaleUpperMiddleQuartile  MaleTopQuartile  \
472                       NaN                        NaN              NaN
7256                     95.0                        5.0             29.0
3449                     96.1                        3.9             99.5
7522                      NaN                        NaN              NaN
6180                     87.0                       13.0             83.0

      FemaleTopQuartile  EmployerSize
472                 NaN    250 to 499
7256               71.0    500 to 999
3449                0.5  1000 to 4999
7522                NaN    250 to 499
6180               17.0    500 to 999
```

[15]:
```
sns.barplot(data=last5_21,
            y = "EmployerName",
            x = 'DiffMedianHourlyPercent',
            orient = "h",
           palette = "gist_heat"
           ).set(title='Top 5 Employers for Women')
```

[15]:
```
[Text(0.5, 1.0, 'Top 5 Employers for Women')]
```



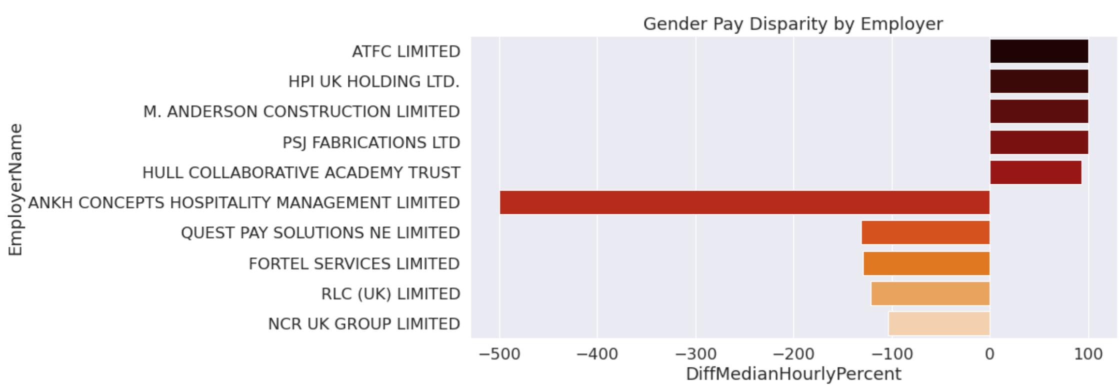
On the flipside, there are employers that appear to largely favor women. However, researching these companies in the visualization it is evident that the gender disparity is heavily influenced by the industry of the employer, as women mostly occupy financing and hospitality jobs.

1.3.1 Data Transformation for Visual Data Exploration

To create a comprehensive visualization, we decided to combine the results from the aforementioned analysis into one graph by merging the two small dataframes we created into one.

[16]:
```
high_low_21 = pd.concat([top5_21, last5_21], axis = 0)
```

[17]:
```
sns.set(rc={'figure.figsize':(12,5.75)}, font_scale = 1.5)
sns.barplot(data=high_low_21,
            y = "EmployerName",
            x = 'DiffMedianHourlyPercent',
            orient = "h",
           palette = "gist_heat"
           ).set(title="Gender Pay Disparity by Employer")

plt.savefig('DiffMedianBar1.pdf')
```



1.4 Data Transformation for Final Analysis

For the final analysis we wanted to observe all of our data in one dataframe. To be able to create visualizations with all three of the datasets we created a column for each containing the year for that dataset. We used this new column to merge each dataframe together into one large dataframe. Now with one large dataframe we went ahead and filled in NAN values with the mean of each column to have data representing each row even if it wasn't provided.

[18]:
```
#ADDING A YEAR COLUMN
gpg_19["Year"] = 2019
gpg_20["Year"] = 2020
gpg_21["Year"] = 2021
```

[19]:
```
#MERGING DATAFRAMES ON THE YEAR COLUMN

merged = pd.concat([gpg_19, gpg_20], axis = 0)
final = pd.concat([merged,gpg_21], axis = 0)
final
```

[19]:
```
                                              EmployerName  \
0      'PRIFYSGOL ABERYSTWYTH' AND 'ABERYSTWYTH UNIVE…
1                          10 TRINITY SQUARE HOTEL LIMITED
2                       1LIFE MANAGEMENT SOLUTIONS LIMITED
3                     1ST CHOICE STAFF RECRUITMENT LIMITED
4                                     1ST HOME CARE LTD.
…                                                      …
10487                                          ZPG LIMITED
10488                   ZURICH EMPLOYMENT SERVICES LIMITED
10489                   ZURICH UK GENERAL SERVICES LIMITED
10490                                        ZUTO LIMITED
10491                     ZWANENBERG FOOD GROUP UK LIMITED

       DiffMeanHourlyPercent  DiffMedianHourlyPercent  DiffMeanBonusPercent  \
0                       11.5                     10.3                   NaN
1                        8.7                     10.3                  29.6
2                       11.0                     -0.5                  81.5
3                       -2.3                      0.0                -114.8
4                       -2.0                      0.5                   NaN
…                        …                        …                     …
10487                   22.4                     22.4                  72.7
10488                   26.5                     24.4                  55.4
10489                   16.7                     19.7                  56.8
10490                   16.0                      6.0                  10.0
10491                   18.7                      2.1                  76.9

       DiffMedianBonusPercent  MaleBonusPercent  FemaleBonusPercent  \
0                         NaN               0.0                 0.0
1                        54.5              90.5                90.5
```

```
2                    94.2            10.0              11.4
3                  -249.3             1.1               0.4
4                     NaN             0.0               0.0
…                     …               …                 …
10487                15.9            16.0              15.0
10488                36.0            96.9              95.5
10489                45.1            97.3              96.7
10490                35.0            66.0              75.0
10491                 0.0            57.7              42.3

       MaleLowerQuartile  FemaleLowerQuartile  MaleLowerMiddleQuartile  \
0                   53.0                 47.0                     41.0
1                   47.9                 52.1                     56.3
2                   49.0                 51.0                     35.3
3                   50.8                 49.2                     67.7
4                   10.0                 90.0                      8.0
…                   …                    …                        …
10487               45.7                 54.3                     52.6
10488               35.9                 64.1                     43.0
10489               41.5                 58.5                     66.8
10490               64.0                 36.0                     58.0
10491               48.7                 51.3                     59.4

       FemaleLowerMiddleQuartile  MaleUpperMiddleQuartile  \
0                           59.0                     40.0
1                           43.7                     78.9
2                           64.7                     42.3
3                           32.3                     62.9
4                           92.0                      9.0
…                           …                        …
10487                       47.4                     57.7
10488                       57.0                     53.1
10489                       33.2                     66.0
10490                       42.0                     71.0
10491                       40.6                     62.3

       FemaleUpperMiddleQuartile  MaleTopQuartile  FemaleTopQuartile  \
0                           60.0             62.0               38.0
1                           21.1             66.7               33.3
2                           57.7             44.2               55.8
3                           37.1             50.0               50.0
4                           91.0              9.0               91.0
…                           …                …                  …
10487                       42.3             70.9               29.1
10488                       46.9             67.8               32.2
10489                       34.0             69.3               30.7
10490                       29.0             70.0               30.0
```

```
10491                       37.7             65.0                35.0

       EmployerSize  Year
0      1000 to 4999  2019
1        250 to 499  2019
2        250 to 499  2019
3        250 to 499  2019
4        250 to 499  2019
…               …     …
10487    500 to 999  2021
10488  1000 to 4999  2021
10489  1000 to 4999  2021
10490    250 to 499  2021
10491    500 to 999  2021

[27945 rows x 17 columns]
```

[20]:

```
#REPLACING NULL VALUES WITH MEANS OF EACH PERCENTILE

meanBonus = final['DiffMeanBonusPercent'].mean()
medianBonus = final['DiffMedianBonusPercent'].mean()
mean_MaleLQ = final['MaleLowerQuartile'].mean()
mean_FemLQ = final['FemaleLowerQuartile'].mean()
mean_MaleLMQ = final['MaleLowerMiddleQuartile'].mean()
mean_FemLMQ = final['FemaleLowerMiddleQuartile'].mean()
mean_MaleUMQ = final['MaleUpperMiddleQuartile'].mean()
mean_FemUMQ = final['FemaleUpperMiddleQuartile'].mean()
mean_MaleTopQ = final['MaleTopQuartile'].mean()
mean_FemTopQ = final['FemaleTopQuartile'].mean()
final['DiffMeanBonusPercent'].fillna(value=meanBonus, inplace=True)
final['DiffMedianBonusPercent'].fillna(value=medianBonus, inplace=True)
final['MaleLowerQuartile'].fillna(value=mean_MaleLQ, inplace=True)
final['FemaleLowerQuartile'].fillna(value=mean_FemLQ, inplace=True)
final['MaleLowerMiddleQuartile'].fillna(value=mean_MaleLMQ, inplace=True)
final['FemaleLowerMiddleQuartile'].fillna(value=mean_FemLMQ, inplace=True)
final['MaleUpperMiddleQuartile'].fillna(value=mean_MaleUMQ, inplace=True)
final['FemaleUpperMiddleQuartile'].fillna(value=mean_FemUMQ, inplace=True)
final['MaleTopQuartile'].fillna(value=mean_MaleTopQ, inplace=True)
final['FemaleTopQuartile'].fillna(value=mean_FemTopQ, inplace=True)
final
```

[20]:

```
                                            EmployerName  \
0      'PRIFYSGOL ABERYSTWYTH' AND 'ABERYSTWYTH UNIVE…
1                         10 TRINITY SQUARE HOTEL LIMITED
2                      1LIFE MANAGEMENT SOLUTIONS LIMITED
3                    1ST CHOICE STAFF RECRUITMENT LIMITED
4                                     1ST HOME CARE LTD.
```

```
…                                          …
10487                            ZPG LIMITED
10488      ZURICH EMPLOYMENT SERVICES LIMITED
10489      ZURICH UK GENERAL SERVICES LIMITED
10490                           ZUTO LIMITED
10491        ZWANENBERG FOOD GROUP UK LIMITED

       DiffMeanHourlyPercent  DiffMedianHourlyPercent  DiffMeanBonusPercent  \
0                       11.5                     10.3             21.101073
1                        8.7                     10.3             29.600000
2                       11.0                     -0.5             81.500000
3                       -2.3                      0.0           -114.800000
4                       -2.0                      0.5             21.101073
…                      …                      …                    …
10487                   22.4                     22.4             72.700000
10488                   26.5                     24.4             55.400000
10489                   16.7                     19.7             56.800000
10490                   16.0                      6.0             10.000000
10491                   18.7                      2.1             76.900000

       DiffMedianBonusPercent  MaleBonusPercent  FemaleBonusPercent  \
0                    3.523732               0.0                 0.0
1                   54.500000              90.5                90.5
2                   94.200000              10.0                11.4
3                 -249.300000               1.1                 0.4
4                    3.523732               0.0                 0.0
…                       …                   …                  …
10487               15.900000              16.0                15.0
10488               36.000000              96.9                95.5
10489               45.100000              97.3                96.7
10490               35.000000              66.0                75.0
10491                0.000000              57.7                42.3

       MaleLowerQuartile  FemaleLowerQuartile  MaleLowerMiddleQuartile  \
0                   53.0                 47.0                     41.0
1                   47.9                 52.1                     56.3
2                   49.0                 51.0                     35.3
3                   50.8                 49.2                     67.7
4                   10.0                 90.0                      8.0
…                  …                    …                       …
10487               45.7                 54.3                     52.6
10488               35.9                 64.1                     43.0
10489               41.5                 58.5                     66.8
10490               64.0                 36.0                     58.0
10491               48.7                 51.3                     59.4

       FemaleLowerMiddleQuartile  MaleUpperMiddleQuartile  \
```

```
0                                  59.0                          40.0
1                                  43.7                          78.9
2                                  64.7                          42.3
3                                  32.3                          62.9
4                                  92.0                           9.0
…                                 …                             …
10487                              47.4                          57.7
10488                              57.0                          53.1
10489                              33.2                          66.0
10490                              42.0                          71.0
10491                              40.6                          62.3

       FemaleUpperMiddleQuartile  MaleTopQuartile  FemaleTopQuartile  \
0                           60.0             62.0               38.0
1                           21.1             66.7               33.3
2                           57.7             44.2               55.8
3                           37.1             50.0               50.0
4                           91.0              9.0               91.0
…                          …                …                  …
10487                       42.3             70.9               29.1
10488                       46.9             67.8               32.2
10489                       34.0             69.3               30.7
10490                       29.0             70.0               30.0
10491                       37.7             65.0               35.0

       EmployerSize  Year
0      1000 to 4999  2019
1        250 to 499  2019
2        250 to 499  2019
3        250 to 499  2019
4        250 to 499  2019
…               …    …
10487    500 to 999  2021
10488  1000 to 4999  2021
10489  1000 to 4999  2021
10490    250 to 499  2021
10491    500 to 999  2021

[27945 rows x 17 columns]
```

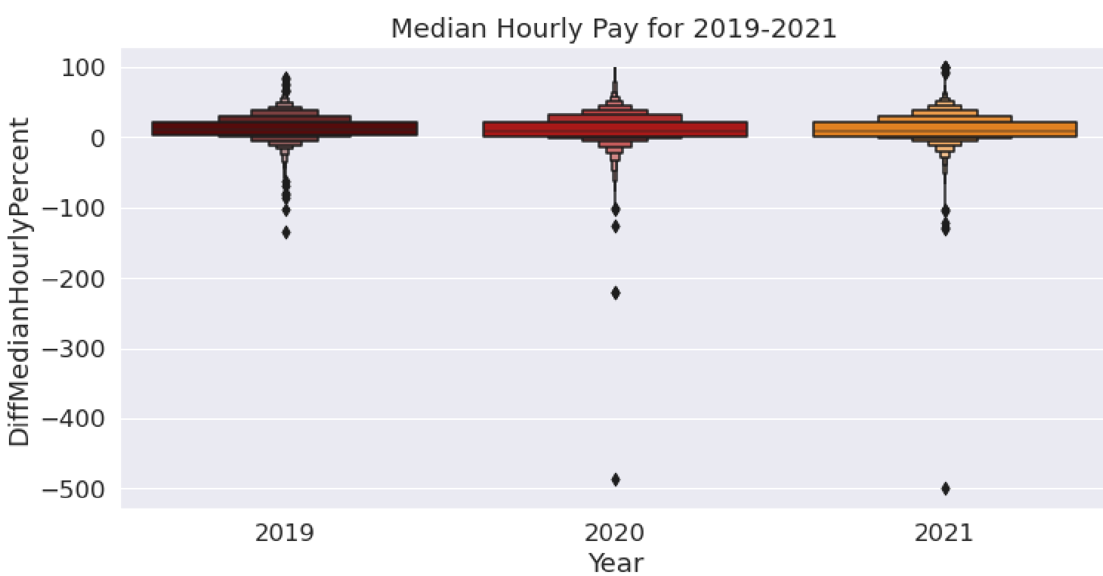
1.5 Data Exploration for Final Analysis

Finally, we wanted to analyze everything we explored so far at a smaller scale now on our final dataframe we created by merging the dataframes for the years 2019, 2020, and 2021. By merging these dataframes on the year column we were able to create visualizations that disply changes over the years, as well as analyze the data using the previously mentioned variables. First we looked at the hourly pay and bonus pay difference over the years, the male to female ratio of hourly pay based on the provided quartile columns, then analyzed the difference in hourly pay based on employer size.

1.5.1 Observing the Gap in Hourly Pay

To start the finalization of our analysis of pay disparity, we created some graphs looking at the difference in median and mean hourly pay, using the boxen plot as used at the start of analysis. With combined dataframes we were able to analyze this variable over the years 2019, 2020, and 2021 without having to measure it against another factor. Next, we created a histogram for the median hourly pay to gain insight of the pay disparity over all three years. We also observed the bonus pay variable to analyze for disparity, focusing on the median difference as the mean difference did not provide significant information.

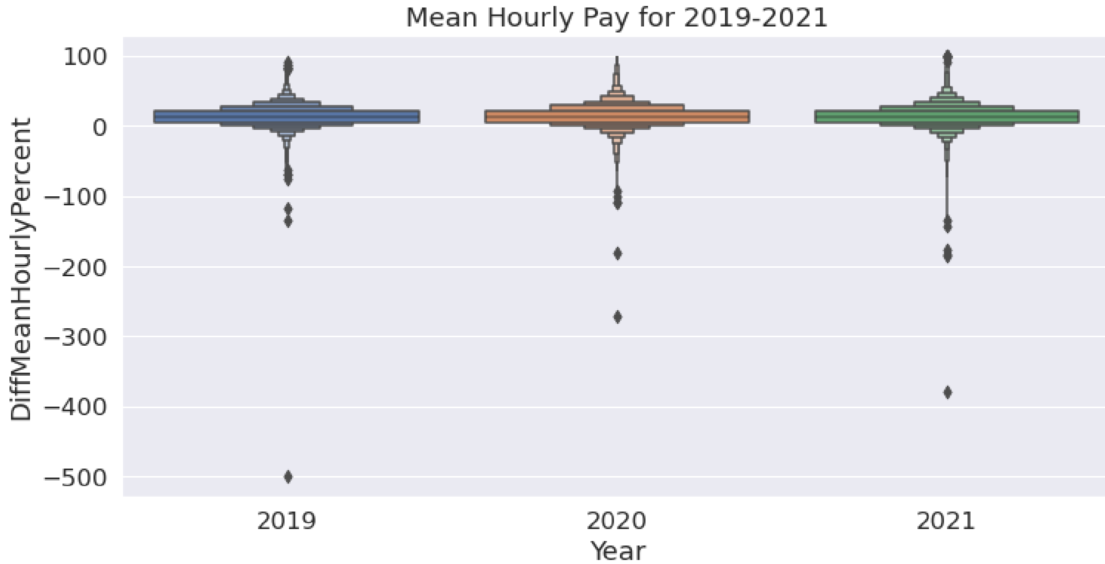
[21]:
```
sns.boxenplot(data=final,
            y = "DiffMedianHourlyPercent",
            x = "Year",
            palette = "gist_heat"
             ).set(title="Median Hourly Pay for 2019-2021")

plt.savefig('DiffMedianYear.pdf')
```



From the above boxen plot we observe that the values above 0 represent men and the values below 0 represent women. From the boxen plot above we can see that between the years 2019 to 2021, the year 2020 has extreme outliers for women when compared to the years 2019 and 2021.

[22]:
```
sns.boxenplot(data=final,
            y = "DiffMeanHourlyPercent",
            x = "Year"
             ).set(title="Mean Hourly Pay for 2019-2021")
```

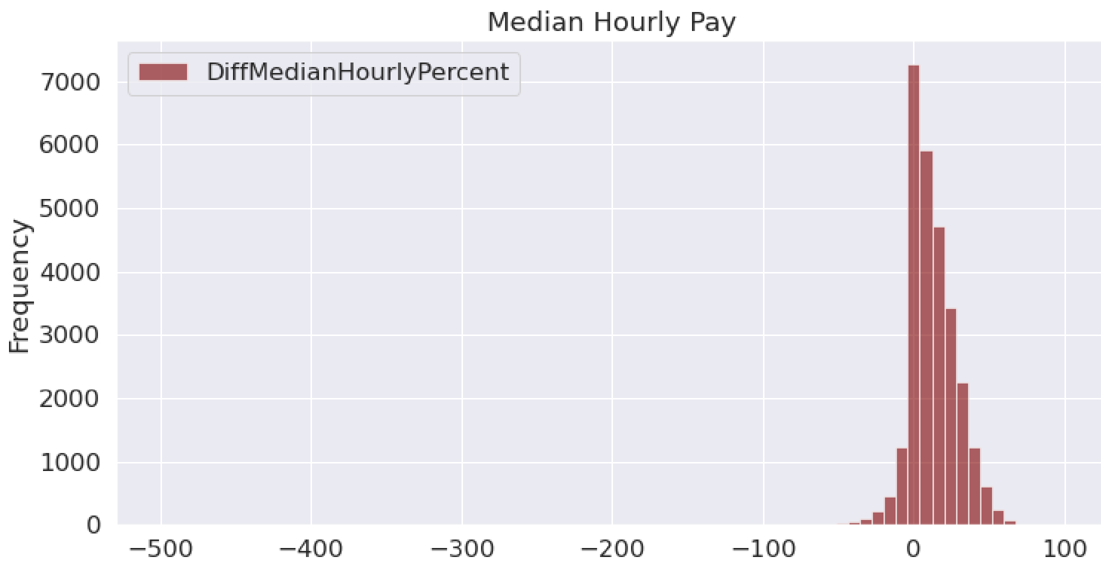
[22]: [Text(0.5, 1.0, 'Mean Hourly Pay for 2019-2021')]



The boxen plot for mean hourly pay shows similar trends like the previous boxen plot where men are favored more than women, with outliers representing some bias towards women. From the boxen plot we can clearly see that in the year 2019, there are more outliers than the other years indicating that in the year 2019 the mean hourly pay was a little more for women compared to 2020 and 2021.

[23]:
```
final['DiffMedianHourlyPercent'].plot(kind='hist',
                                      bins=75,
                                      figsize=[12,6],
                                      alpha=.6,
                                      legend=True,
                                      color = 'maroon'
                                     ).set(title="Median Hourly Pay")
```

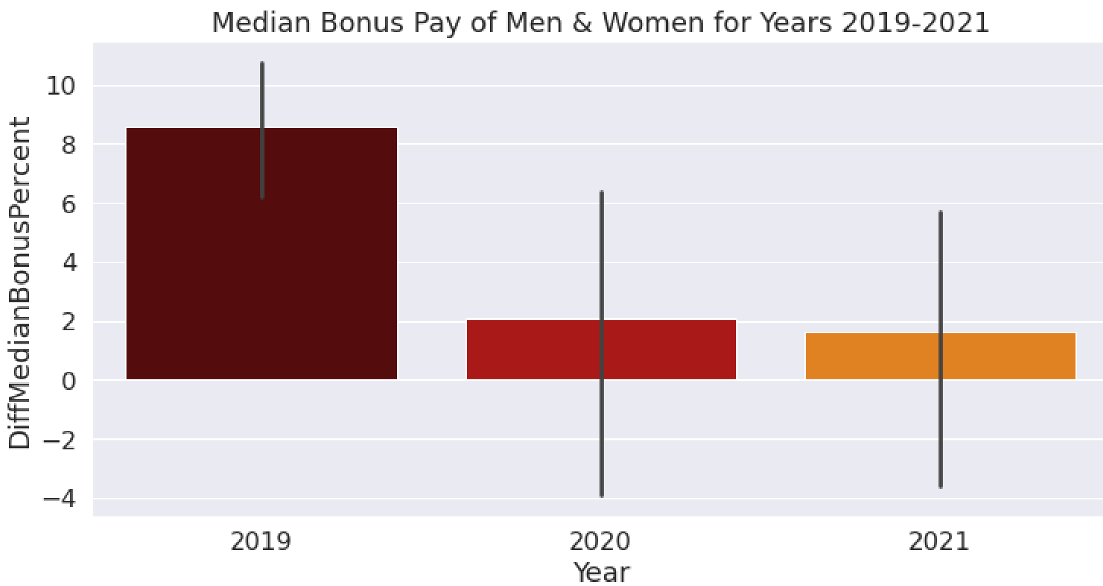
[23]: [Text(0.5, 1.0, 'Median Hourly Pay')]



From the above histogram, we observe that the distribution of the difference in median hourly pay is severely-skewed to the left. Thus, we can infer that in most cases, men have higher hourly pay compared to women.

1.5.2 Bonus Pay

[24]:
```
sns.barplot(data=final,
            y = "DiffMedianBonusPercent",
            x = "Year",
            palette = "gist_heat"
           ).set(title="Median Bonus Pay of Men & Women for Years 2019-2021")
plt.savefig('YearDiffMedBonus.pdf')
```



For 2019, we can observe that the percentage of median bonus pay is skewed towards men and that the ones for women aren't included in the plot. In 2020, it can be seen that the median of women receiving bonus pay is 3% comparatively lower than men. Following that, in 2021, the median of women receiving bonus pay was 2% bonus. Thus, based on this output, we can infer that there is a slight improvement in the probability that women will receive bonus pay.

1.5.3 Male to Female Ratio of Hourly Pay

Next, we wanted to analyze the overall male to female hourly pay ratio of all three years together. To do this we calculated the average percentage of men and women in each quartile, assigning each value to a variable. We then used each variable to create a table to show two columns labeled male and female with each row showing the labeled quartile. By observing the table below, it is concluded that overall more men are in the top hourly pay quartile at 59.7% and more women are in the lower hourly pay quartile at 54.6%.

[25]:
```
#FINDING THE MEANS FOR EACH PERCENTILE

MLQ_per = final['MaleLowerQuartile'].mean()
FLQ_per = final['FemaleLowerQuartile'].mean()
MaleLMQ_per = final['MaleLowerMiddleQuartile'].mean()
FemLMQ_per = final['FemaleLowerMiddleQuartile'].mean()
MaleUMQ_per = final['MaleUpperMiddleQuartile'].mean()
FemUMQ_per = final['FemaleUpperMiddleQuartile'].mean()
MaleTop_per = final['MaleTopQuartile'].mean()
FemTop_per = final['FemaleTopQuartile'].mean()
```

[26]:
```
data = [{'Male': MLQ_per, 'Female': FLQ_per},
        {'Male': MaleLMQ_per , 'Female': FemLMQ_per},
```

```
        {'Male': MaleUMQ_per , 'Female':FemUMQ_per},
        {'Male': MaleTop_per, 'Female': FemTop_per}]
percent= pd.DataFrame(data, index=["Lower_Quartile",
                                   "LowerMiddle_Quartile",
                                   "UpperMiddle_Quartile",
                                   "Top_Quartile"])
percent
```

[26]:

	Male	Female
Lower_Quartile	45.353374	54.646626
LowerMiddle_Quartile	49.841387	50.158613
UpperMiddle_Quartile	54.243593	45.756407
Top_Quartile	59.742682	40.257318

1.5.4 Gender Disparity by Employer

To continue our analysis we looked at a sample of employers, again at each extreme, with 5 employers who had the highest median hourly pay for men and the 5 employers who had the highest median hourly pay for women with all three years combined. We created one comprehensive bar plot using the same strategy used earlier in analysis.

[27]:
```
final.small = final.nsmallest(5, 'DiffMedianHourlyPercent')
final.large = final.nlargest(5, 'DiffMedianHourlyPercent')
final.highlow = pd.concat([final.small,final.large], axis = 0)
```

```
/tmp/ipykernel_55/3621132997.py:1: UserWarning: Pandas doesn't allow columns to
be created via a new attribute name - see https://pandas.pydata.org/pandas-
docs/stable/indexing.html#attribute-access
  final.small = final.nsmallest(5, 'DiffMedianHourlyPercent')
/tmp/ipykernel_55/3621132997.py:2: UserWarning: Pandas doesn't allow columns to
be created via a new attribute name - see https://pandas.pydata.org/pandas-
docs/stable/indexing.html#attribute-access
  final.large = final.nlargest(5, 'DiffMedianHourlyPercent')
/tmp/ipykernel_55/3621132997.py:3: UserWarning: Pandas doesn't allow columns to
be created via a new attribute name - see https://pandas.pydata.org/pandas-
docs/stable/indexing.html#attribute-access
  final.highlow = pd.concat([final.small,final.large], axis = 0)
```

[28]:
```
final.highlow
```

[28]:

	EmployerName	DiffMeanHourlyPercent \
472	ANKH CONCEPTS HOSPITALITY MANAGEMENT LIMITED	-379.6
6518	NSS CLEANING LIMITED	-181.3
726	AUTO-SLEEPERS GROUP LIMITED	-42.5
727	AUTO-SLEEPERS INVESTMENTS LIMITED	-42.5
1747	DONALDSON TIMBER ENGINEERING LIMITED	-54.2
989	BEERE ELECTRICAL SERVICES LIMITED	100.0

4057	HARVEY NICHOLS (OWN BRAND) STORES LIMITED	100.0
4061	HARVEY NICHOLS RESTAURANTS LIMITED	100.0
4702	J.C.B.EARTHMOVERS LIMITED	100.0
4715	J5C MANAGEMENT LIMITED	100.0

	DiffMedianHourlyPercent	DiffMeanBonusPercent	DiffMedianBonusPercent \
472	-499.5	21.101073	3.523732
6518	-487.2	-9087.300000	-14967.100000
726	-220.3	10.300000	-5.900000
727	-220.3	10.300000	-5.900000
1747	-134.0	-39.500000	-393.500000
989	100.0	100.000000	100.000000
4057	100.0	56.600000	46.700000
4061	100.0	21.101073	3.523732
4702	100.0	28.300000	0.000000
4715	100.0	41.300000	23.000000

	MaleBonusPercent	FemaleBonusPercent	MaleLowerQuartile \
472	0.0	0.0	45.353374
6518	12.3	5.3	98.200000
726	52.2	29.5	100.000000
727	52.2	29.5	100.000000
1747	72.0	75.0	97.900000
989	57.1	0.0	100.000000
4057	22.2	56.9	100.000000
4061	0.0	3.2	100.000000
4702	96.1	90.9	45.353374
4715	6.4	7.4	100.000000

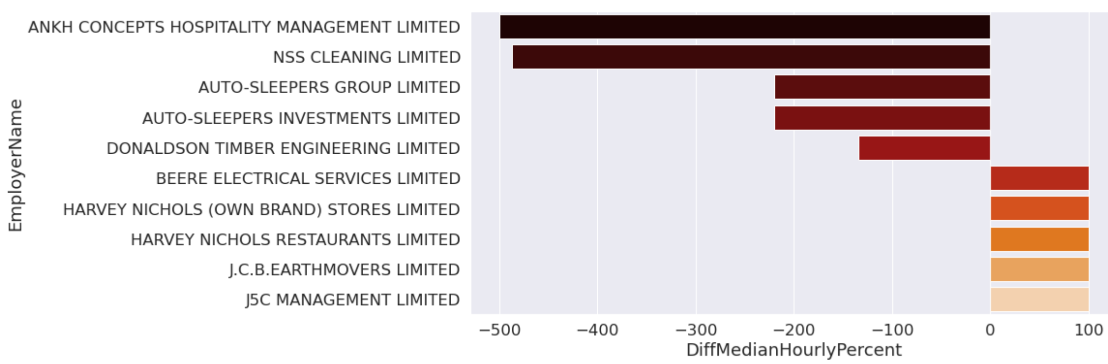
	FemaleLowerQuartile	MaleLowerMiddleQuartile	FemaleLowerMiddleQuartile \
472	54.646626	49.841387	50.158613
6518	1.800000	100.000000	0.000000
726	0.000000	50.000000	50.000000
727	0.000000	50.000000	50.000000
1747	2.100000	98.900000	1.100000
989	0.000000	100.000000	0.000000
4057	0.000000	100.000000	0.000000
4061	0.000000	100.000000	0.000000
4702	54.646626	49.841387	50.158613
4715	0.000000	100.000000	0.000000

	MaleUpperMiddleQuartile	FemaleUpperMiddleQuartile	MaleTopQuartile \
472	54.243593	45.756407	59.742682
6518	100.000000	0.000000	67.300000
726	0.000000	100.000000	100.000000
727	0.000000	100.000000	100.000000
1747	78.900000	21.100000	76.600000

989	100.000000	0.000000	100.000000
4057	100.000000	0.000000	100.000000
4061	100.000000	0.000000	100.000000
4702	54.243593	45.756407	59.742682
4715	100.000000	0.000000	100.000000

	FemaleTopQuartile	EmployerSize	Year
472	40.257318	250 to 499	2021
6518	32.700000	250 to 499	2020
726	0.000000	250 to 499	2020
727	0.000000	250 to 499	2020
1747	23.400000	250 to 499	2019
989	0.000000	Less than 250	2020
4057	0.000000	Not Provided	2020
4061	0.000000	Not Provided	2020
4702	40.257318	250 to 499	2020
4715	0.000000	500 to 999	2020

[29]:
```
sns.barplot(data=final.highlow,
            y = "EmployerName",
            x = 'DiffMedianHourlyPercent',
            orient = "h",
           palette = "gist_heat")
plt.savefig('EmpDiff.pdf')
```



The bar plot represents the the 5 largest and 5 smallest Hourly median pay across various companies between the years 2019 and 2021. We can see that the companies to the left of 0 represent the companies which favor women over men as they have large negative values. The companies to the right of 0 represent companies with positive Median values which represent men getting paid more . From the above bar plot we can clearly see the companies that women would prefer to work in.

1.5.5 Gender Pay Disparity by Employer Size

Lastly, we analyzed the overall pay disparity based on employer size, focusing on the difference in the average hourly pay of men and women.

[30]:
```
sns.set(rc={'figure.figsize':(16.75,8)}, font_scale = 1.5)
sns.boxenplot(data=final,
              x = "EmployerSize",
              y = "DiffMeanHourlyPercent",
              order = ["Less than 250", "250 to 499", "500 to 999", "1000 to␣
↪4999",
                        "5000 to 19,999", "20,000 or more", "Not Provided"],
              palette = "gist_heat"
             ).set(title="Mean Hourly Pay Based on Employer Size")
```

[30]: [Text(0.5, 1.0, 'Mean Hourly Pay Based on Employer Size')]

From the boxen plot above we can observe that the average hourly pay for women is higher in companies with less number of employees. Companies where the number of employees are larger tend to favor men more than women according to the boxen plot

1.6 Conclusion

After our analysis we came to a series of conclusions based on our results. By looking at the disparity in hourly pay, it is possible the increase in gender diversity also displays an increase in pay disparity with the outliers, women receiving a higher hourly pay, becoming more frequent. This possibility would actually be a positive outcome as it implies increased equity that cannot be as easily observed through the data we were using. Employers with less employees may be benefical for women receiving a higher hourly pay. Although the analysis still showed men received on average a higher hourly pay, the possibility of women recieving equitable income is more likely. Overall men make more hourly pay compared to women, with women more likely to make much less than men. The industry of the employer affects the gender diversity amongst companies, and as a result this showed extreme results with gender pay disparity. Men are more likely to receive bonus pay over women, however, the dominance of men receiving bonuses over women has decreased, likely because of the pandemic. The bonus pay women receive present as outliers compared to the range at which men receive bonuses, affecting the probability range of men or women receiving a bonus by a sigificant amount.