In [1]:
```
#Data Analysis Libraries
import numpy as np
import pandas as pd

#Visualisation Libraries
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

#Ignore Warnings
import warnings
warnings.filterwarnings('ignore')

#Google Colab Import Files
from google.colab import files
import io
```

In [2]:
```
uploaded = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving nomis_2024_03_04_132215.csv to nomis_2024_03_04_132215.csv
Saving NS-SEC_2021.csv to NS-SEC_2021.csv
Saving table-1-2020-21.csv to table-1-2020-21.csv
```

In [3]:
```
GradData = pd.read_csv('table-1-2020-21.csv')
AreaQuali = pd.read_csv('nomis_2024_03_04_132215.csv')
SERank = pd.read_csv('NS-SEC_2021.csv')
```

In [4]:
```
print(GradData.columns)
print(AreaQuali.columns)
print(SERank.columns)
```

```
Index(['UKPRN', 'Provider name', 'Country of provider', 'Domicile',
       'Level of qualification obtained', 'Mode of former study',
       'Interim study', 'Sex', 'Activity', 'Academic year', 'Number'],
      dtype='object')
Index(['2022 local authorities: county', 'No qualifications',
       'Level 1 and entry level qualifications', 'Level 2 qualifications',
       'Apprenticeship', 'Level 3 qualifications',
       'Level 4 qualifications or above', 'Other qualifications', 'Unnamed: 8',
       'Unnamed: 9'],
      dtype='object')
Index(['ONSConstID', 'ConstituencyName', 'RegNationID', 'RegNationName',
       'NatComparator', 'variables', 'groups', 'Con_num', 'Con_pc', 'RN_pc',
       'Nat_pc', 'ranking_total', 'rank'],
      dtype='object')
```

In [5]:
```
AreaQuali = AreaQuali.drop(['Unnamed: 8'], axis = 1)
AreaQuali = AreaQuali.drop(['Unnamed: 9'], axis = 1)
```

In [6]:
```
GradData.astype('string')
AreaQuali.astype('string')
SERank.astype('string')
```

Out[6]:

	ONSConstID	ConstituencyName	RegNationID	RegNationName	NatComparator	variab
0	E14000530	Aldershot	E12000008	South East	England & Wales	High manager administrat and profes
1	E14000530	Aldershot	E12000008	South East	England & Wales	Lov manager administrat a professi
2	E14000530	Aldershot	E12000008	South East	England & Wales	Intermedi occupatic
3	E14000530	Aldershot	E12000008	South East	England & Wales	Sm employ and o accou work
4	E14000530	Aldershot	E12000008	South East	England & Wales	Lov supervis and techni occupatic
...	...	...	...	...	...	
5152	W07000080	Cardiff South and Penarth	W92000004	Wales	England & Wales	Lov supervis and techni occupatic
5153	W07000080	Cardiff South and Penarth	W92000004	Wales	England & Wales	Semi-routi occupatic
5154	W07000080	Cardiff South and Penarth	W92000004	Wales	England & Wales	Routi occupatic
5155	W07000080	Cardiff South and Penarth	W92000004	Wales	England & Wales	Never work / long-te unemploy
5156	W07000080	Cardiff South and Penarth	W92000004	Wales	England & Wales	Full-ti studer

5157 rows × 13 columns

In [7]:
```
AreaQuali['No qualifications'].astype('int')
AreaQuali['Level 1 and entry level qualifications'].astype('int')
AreaQuali['Level 2 qualifications'].astype('int')
AreaQuali['Apprenticeship'].astype('int')
AreaQuali['Level 3 qualifications'].astype('int')
AreaQuali['Level 4 qualifications or above'].astype('int')
AreaQuali['Other qualifications'].astype('int')
```

Out[7]:
```
0       789
1      3199
2       602
3      1034
4      1906
       ...
169    1412
170     586
171     735
172     584
173    1597
Name: Other qualifications, Length: 174, dtype: int64
```

In [8]:
```
SERank['rank'].astype('int')
SERank['ranking_total'].astype('float')
```

Out[8]:
```
0       0.337408
1       0.337408
2       0.230380
3       0.230380
4       0.303069
          ...
5152    0.278226
5153    0.278226
5154    0.278226
5155    0.106746
5156    0.092428
Name: ranking_total, Length: 5157, dtype: float64
```

In [9]:
```
GradData.describe(include = "all")
```

Out[9]:

	UKPRN	Provider name	Country of provider	Domicile	Level of qualification obtained	Mode of former study	Interim study	Sex
count	1.048561e+06	1048561	1048561	1048561	1048561	1048561	1048561	1048561
unique	NaN	340	5	4	3	3	2	4
top	NaN	The Open University	All	All	All	All	Include significant interim study	All
freq	NaN	6656	522880	409663	405997	394115	524862	329004
mean	1.000964e+07	NaN	NaN	NaN	NaN	NaN	NaN	NaN
std	1.331511e+04	NaN	NaN	NaN	NaN	NaN	NaN	NaN
min	1.000006e+07	NaN	NaN	NaN	NaN	NaN	NaN	NaN
25%	1.000386e+07	NaN	NaN	NaN	NaN	NaN	NaN	NaN
50%	1.000714e+07	NaN	NaN	NaN	NaN	NaN	NaN	NaN
75%	1.000782e+07	NaN	NaN	NaN	NaN	NaN	NaN	NaN
max	1.008659e+07	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [10]:
```
GradData.head()
```

Out[10]:

	UKPRN	Provider name	Country of provider	Domicile	Level of qualification obtained	Mode of former study	Interim study	Sex	Ac
0	10008071	AA School of Architecture	England	Non-UK	All	Full-time	Exclude significant interim study	Female	Full employ
1	10008071	AA School of Architecture	England	Non-UK	All	Full-time	Exclude significant interim study	Female	Part employ
2	10008071	AA School of Architecture	England	Non-UK	All	Full-time	Exclude significant interim study	Female	Unk patte employ
3	10008071	AA School of Architecture	England	Non-UK	All	Full-time	Exclude significant interim study	Female	Volunt unpaid
4	10008071	AA School of Architecture	England	Non-UK	All	Full-time	Exclude significant interim study	Female	Employmer further

In [11]:
```
AreaQuali.describe(include = "all")
```

Out[11]:

	2022 local authorities: county	No qualifications	Level 1 and entry level qualifications	Level 2 qualifications	Apprenticeship	Level 3 qualifications	
count	174	174.000000	174.000000	174.000000	174.000000	174.000000	
unique	174	NaN	NaN	NaN	NaN	NaN	
top	Darlington	NaN	NaN	NaN	NaN	NaN	
freq	1	NaN	NaN	NaN	NaN	NaN	
mean	NaN	13713.195402	13821.396552	20142.356322	7447.798851	29858.931034	
std	NaN	10604.969794	12443.469521	18300.281003	6565.655899	26931.198757	
min	NaN	61.000000	77.000000	170.000000	38.000000	255.000000	
25%	NaN	6665.750000	6540.000000	9446.000000	3592.250000	14637.500000	
50%	NaN	11037.500000	10131.000000	13420.000000	5103.000000	19999.000000	
75%	NaN	17239.750000	15180.750000	22032.500000	8482.000000	34047.500000	
max	NaN	60591.000000	77586.000000	113671.000000	36082.000000	150678.000000	2

In [12]:
```
AreaQuali.head()
```

Out[12]:

	2022 local authorities: county	No qualifications	Level 1 and entry level qualifications	Level 2 qualifications	Apprenticeship	Level 3 qualifications	qua
0	Darlington	4306	4190	6925	2845	11297	
1	County Durham	19076	19757	33256	12329	51751	
2	Hartlepool	3450	3108	5649	2250	9155	
3	Middlesbrough	6289	4950	7551	3215	11811	
4	Northumberland	9939	12398	20706	8349	32548	

In [13]:
```
SERank.describe(include = "all")
```

Out[13]:

	ONSConstID	ConstituencyName	RegNationID	RegNationName	NatComparator	varia
count	5157	5157	5157	5157	5157	
unique	573	573	10	10	1	
top	E14000530	Aldershot	E12000008	South East	England & Wales	Hi manag administr and prof
freq	9	9	756	756	5157	
mean	NaN	NaN	NaN	NaN	NaN	
std	NaN	NaN	NaN	NaN	NaN	
min	NaN	NaN	NaN	NaN	NaN	
25%	NaN	NaN	NaN	NaN	NaN	
50%	NaN	NaN	NaN	NaN	NaN	
75%	NaN	NaN	NaN	NaN	NaN	
max	NaN	NaN	NaN	NaN	NaN	

In [14]:
```
SERank.head()
```

Out[14]:

	ONSConstID	ConstituencyName	RegNationID	RegNationName	NatComparator	variables
0	E14000530	Aldershot	E12000008	South East	England & Wales	Higher managerial, administrative and professi...
1	E14000530	Aldershot	E12000008	South East	England & Wales	Lower managerial, administrative and professio...
2	E14000530	Aldershot	E12000008	South East	England & Wales	Intermediate occupations
3	E14000530	Aldershot	E12000008	South East	England & Wales	Small employers and own account workers
4	E14000530	Aldershot	E12000008	South East	England & Wales	Lower supervisory and technical occupations

In [15]:
```
GradData = GradData.drop(['UKPRN'], axis = 1)
GradData = GradData.drop(['Country of provider'], axis = 1)
GradData = GradData.drop(['Domicile'], axis = 1)
GradData = GradData.drop(['Interim study'], axis = 1)
GradData = GradData.drop(['Sex'], axis = 1)
GradData = GradData.drop(['Academic year'], axis = 1)
```

In [16]:
```
GradData.rename(columns={'Number': 'Total'}, inplace=True)
```

In [17]:
```
SERank = SERank.drop(['ONSConstID'], axis = 1)
SERank = SERank.drop(['RegNationID'], axis = 1)
SERank = SERank.drop(['NatComparator'], axis = 1)
SERank = SERank.drop(['variables'], axis = 1)
SERank = SERank.drop(['Con_num'], axis = 1)
SERank = SERank.drop(['Con_pc'], axis = 1)
SERank = SERank.drop(['RN_pc'], axis = 1)
SERank = SERank.drop(['Nat_pc'], axis = 1)
```

In [18]:
```
AreaQuali.set_index('2022 local authorities: county', inplace=True)
AreaQuali = AreaQuali.stack().to_frame('Total').reset_index()
AreaQuali.rename(columns={'level_1':'Qualification Type'},inplace=True)
```

In [19]:
```
GradData['Activity'].unique()
```

Out[19]:
```
array(['Full-time employment', 'Part-time employment',
       'Unknown pattern of employment', 'Voluntary or unpaid work',
       'Employment\xa0and further study', 'Full-time further study',
       'Part-time further study', 'Unknown pattern of further study',
       'Other including travel, caring for someone or retired',
       'Unemployed', 'Total with known outcomes', 'Non-respondents',
       'Total'], dtype=object)
```

In [20]:
```
maskA = GradData['Activity'] == 'Total with known outcomes'
maskB = GradData['Activity'] == 'Total'
```

```
maskC = GradData['Activity'] == 'Non-respondents'

GradData = GradData[~maskA]
GradData = GradData[~maskB]
GradData = GradData[~maskC]
```

In [21]:
```
combine = [GradData]

for dataset in combine:
    dataset['Activity'] = dataset['Activity'].replace(['Full-time employment', 'Par
    dataset['Activity'] = dataset['Activity'].replace(['Full-time further study', '
    dataset['Activity'] = dataset['Activity'].replace(['Employment\xa0and further s
    dataset['Activity'] = dataset['Activity'].replace(['Other including travel, car
```

In [22]:
```
AreaQuali['Qualification Type'].unique()
```

Out[22]:
```
array(['No qualifications', 'Level 1 and entry level qualifications',
       'Level 2 qualifications', 'Apprenticeship',
       'Level 3 qualifications', 'Level 4 qualifications or above',
       'Other qualifications'], dtype=object)
```

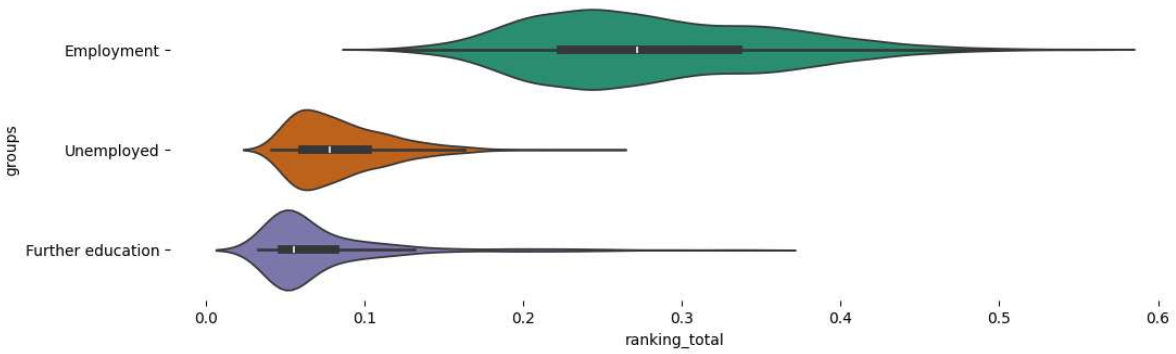
In [23]:
```
combine = [AreaQuali]

for dataset in combine:
    dataset['Qualification Type'] = dataset['Qualification Type'].replace(['Level 1
```

In [24]:
```
SERank['groups'].unique()
```

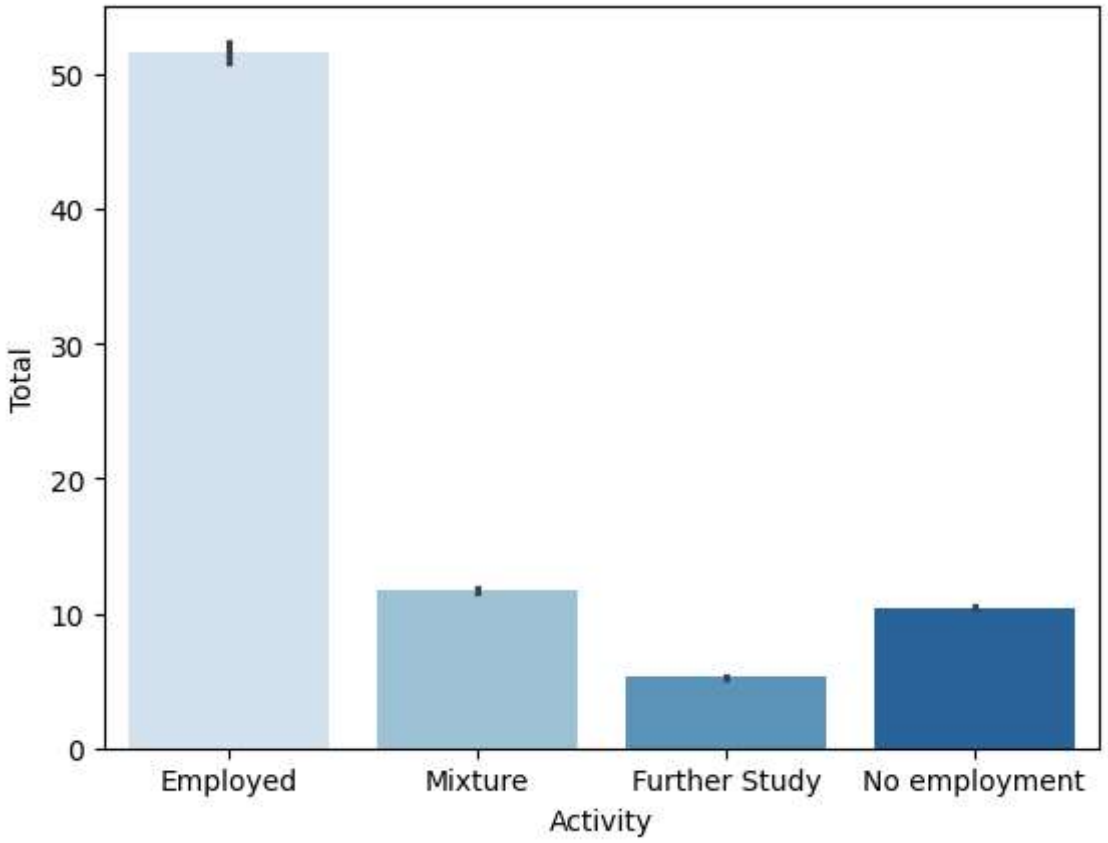
Out[24]:
```
array(['Managerial, administrative and professional occupations',
       'Intermediate occupations', 'Routine and manual occupations',
       'Never worked / long-term unemployed', 'Full-time students'],
      dtype=object)
```

In [25]:
```
combine = [SERank]

for dataset in combine:
    dataset['groups'] = dataset['groups'].replace(['Managerial, administrative and
    dataset['groups'] = dataset['groups'].replace('Never worked / long-term unemplo
    dataset['groups'] = dataset['groups'].replace('Full-time students', 'Further ed
```

In [26]:
```
figsize = (12, 1.2 * len(SERank['groups'].unique()))
plt.figure(figsize=figsize)
sns.violinplot(SERank, x='ranking_total', y='groups', inner='box', palette='Dark2')
sns.despine(top=True, right=True, bottom=True, left=True)
```



In [27]:
```
sns.barplot(x = "Activity", y = "Total", data = GradData, palette = "Blues")
plt.show()
```



In [28]:
```
top5rn = SERank.sort_values(by=['rank']).head(5)
bottom5rn = SERank.sort_values(by=['rank']).tail(5)

print(top5rn)
print(bottom5rn)
```

```
           ConstituencyName             RegNationName             groups  \
3041        Nottingham South             East Midlands  Further education
172                Battersea                    London         Employment
171                Battersea                    London         Employment
304   Birmingham, Hodge Hill             West Midlands         Unemployed
1678          Great Grimsby  Yorkshire and The Humber         Employment

      ranking_total  rank
3041       0.345145     1
172        0.556306     1
171        0.556306     1
304        0.247469     1
1678       0.458726     1
           ConstituencyName    RegNationName            groups  \
3300          Richmond Park           London        Employment
224       Berwick-upon-Tweed       North East  Further education
2833   North East Hampshire       South East        Unemployed
297   Birmingham, Hodge Hill    West Midlands        Employment
785                Cambridge  East of England        Employment

      ranking_total  rank
3300       0.114850   573
224        0.032813   573
2833       0.041182   573
297        0.136152   573
785        0.129088   573
```

In [29]:
```
top5rt = SERank.sort_values(by=['ranking_total']).tail(5)
bottom5rt = SERank.sort_values(by=['ranking_total']).head(5)
```

```
print(top5rt)
print(bottom5rt)
```

```
     ConstituencyName RegNationName      groups  ranking_total  rank
4590        Wimbledon        London  Employment       0.542545     3
3295    Richmond Park        London  Employment       0.551775     2
3294    Richmond Park        London  Employment       0.551775     2
172         Battersea        London  Employment       0.556306     1
171         Battersea        London  Employment       0.556306     1
          ConstituencyName    RegNationName            groups  ranking_total  \
224     Berwick-upon-Tweed       North East  Further education       0.032813
2870         North Norfolk  East of England  Further education       0.033315
1016               Clacton  East of England  Further education       0.035385
2420  Louth and Horncastle    East Midlands  Further education       0.036881
2969    North West Norfolk  East of England  Further education       0.037842

      rank
224    573
2870   572
1016   571
2420   570
2969   569
```

In [30]:
```
AreaQuali['2022 local authorities: county'].unique()
```

Out[30]:
```
array(['Darlington', 'County Durham', 'Hartlepool', 'Middlesbrough',
       'Northumberland', 'Redcar and Cleveland', 'Stockton-on-Tees',
       'Gateshead', 'Newcastle upon Tyne', 'North Tyneside',
       'South Tyneside', 'Sunderland', 'Blackburn with Darwen',
       'Blackpool', 'Cheshire East', 'Cheshire West and Chester',
       'Halton', 'Warrington', 'Cumbria', 'Bolton', 'Bury', 'Manchester',
       'Oldham', 'Rochdale', 'Salford', 'Stockport', 'Tameside',
       'Trafford', 'Wigan', 'Lancashire', 'Knowsley', 'Liverpool',
       'Sefton', 'St. Helens', 'Wirral', 'East Riding of Yorkshire',
       'Kingston upon Hull, City of', 'North East Lincolnshire',
       'North Lincolnshire', 'York', 'North Yorkshire', 'Barnsley',
       'Doncaster', 'Rotherham', 'Sheffield', 'Bradford', 'Calderdale',
       'Kirklees', 'Leeds', 'Wakefield', 'Derby', 'Leicester',
       'Nottingham', 'Rutland', 'Derbyshire', 'Leicestershire',
       'Lincolnshire', 'Nottinghamshire', 'North Northamptonshire',
       'West Northamptonshire', 'Herefordshire, County of', 'Shropshire',
       'Stoke-on-Trent', 'Telford and Wrekin', 'Staffordshire',
       'Warwickshire', 'Birmingham', 'Coventry', 'Dudley', 'Sandwell',
       'Solihull', 'Walsall', 'Wolverhampton', 'Worcestershire',
       'Bedford', 'Central Bedfordshire', 'Luton', 'Peterborough',
       'Southend-on-Sea', 'Thurrock', 'Cambridgeshire', 'Essex',
       'Hertfordshire', 'Norfolk', 'Suffolk', 'Camden', 'City of London',
       'Hackney', 'Hammersmith and Fulham', 'Haringey', 'Islington',
       'Kensington and Chelsea', 'Lambeth', 'Lewisham', 'Newham',
       'Southwark', 'Tower Hamlets', 'Wandsworth', 'Westminster',
       'Barking and Dagenham', 'Barnet', 'Bexley', 'Brent', 'Bromley',
       'Croydon', 'Ealing', 'Enfield', 'Greenwich', 'Harrow', 'Havering',
       'Hillingdon', 'Hounslow', 'Kingston upon Thames', 'Merton',
       'Redbridge', 'Richmond upon Thames', 'Sutton', 'Waltham Forest',
       'Bracknell Forest', 'Brighton and Hove', 'Isle of Wight', 'Medway',
       'Milton Keynes', 'Portsmouth', 'Reading', 'Slough', 'Southampton',
       'West Berkshire', 'Windsor and Maidenhead', 'Wokingham',
       'Buckinghamshire', 'East Sussex', 'Hampshire', 'Kent',
       'Oxfordshire', 'Surrey', 'West Sussex',
       'Bath and North East Somerset', 'Bristol, City of', 'Cornwall',
       'Isles of Scilly', 'North Somerset', 'Plymouth',
       'Bournemouth, Christchurch and Poole', 'South Gloucestershire',
       'Swindon', 'Torbay', 'Wiltshire', 'Devon', 'Dorset',
       'Gloucestershire', 'Somerset', 'Isle of Anglesey', 'Gwynedd',
       'Conwy', 'Denbighshire', 'Flintshire', 'Wrexham', 'Powys',
       'Ceredigion', 'Pembrokeshire', 'Carmarthenshire', 'Swansea',
       'Neath Port Talbot', 'Bridgend', 'Vale of Glamorgan', 'Cardiff',
       'Rhondda Cynon Taff', 'Merthyr Tydfil', 'Caerphilly',
       'Blaenau Gwent', 'Torfaen', 'Monmouthshire', 'Newport'],
      dtype=object)
```

In [31]:
```
Nott = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Nottinghamshire']
Mert = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Merton']
Brum = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Birmingham']
NELinc = AreaQuali[AreaQuali['2022 local authorities: county'] == 'North East Lincc

Top5rn = pd.concat([Nott, Mert, Brum, NELinc], ignore_index=True)
Top5rn
```

Out[31]:

	2022 local authorities: county	Qualification Type	Total
0	Nottinghamshire	No qualifications	32562
1	Nottinghamshire	Other qualifications	36725
2	Nottinghamshire	Other qualifications	54099
3	Nottinghamshire	Apprenticeship	21070
4	Nottinghamshire	Other qualifications	82962
5	Nottinghamshire	Level 4 qualifications or above	144056
6	Nottinghamshire	Other qualifications	6788
7	Merton	No qualifications	8956
8	Merton	Other qualifications	6526
9	Merton	Other qualifications	7942
10	Merton	Apprenticeship	3309
11	Merton	Other qualifications	13453
12	Merton	Level 4 qualifications or above	66101
13	Merton	Other qualifications	2925
14	Birmingham	No qualifications	51860
15	Birmingham	Other qualifications	39489
16	Birmingham	Other qualifications	50221
17	Birmingham	Apprenticeship	15585
18	Birmingham	Other qualifications	73407
19	Birmingham	Level 4 qualifications or above	180826
20	Birmingham	Other qualifications	10082
21	North East Lincolnshire	No qualifications	8121
22	North East Lincolnshire	Other qualifications	8120
23	North East Lincolnshire	Other qualifications	11793
24	North East Lincolnshire	Apprenticeship	4097
25	North East Lincolnshire	Other qualifications	14612
26	North East Lincolnshire	Level 4 qualifications or above	18869
27	North East Lincolnshire	Other qualifications	1497

In [32]:

```
Rich = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Richmond upon Tham
Nland = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Northumberland']
NNshire = AreaQuali[AreaQuali['2022 local authorities: county'] == 'North Northampt
Brum = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Birmingham']
Camb = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Cambridgeshire']

Bottom5rn = pd.concat([Rich, Nland, NNshire, Brum, Camb], ignore_index=True)
Bottom5rn
```

Out[32]:

	2022 local authorities: county	Qualification Type	Total
0	Richmond upon Thames	No qualifications	3751
1	Richmond upon Thames	Other qualifications	3523
2	Richmond upon Thames	Other qualifications	5500
3	Richmond upon Thames	Apprenticeship	1804
4	Richmond upon Thames	Other qualifications	10829
5	Richmond upon Thames	Level 4 qualifications or above	68908
6	Richmond upon Thames	Other qualifications	1409
7	Northumberland	No qualifications	9939
8	Northumberland	Other qualifications	12398
9	Northumberland	Other qualifications	20706
10	Northumberland	Apprenticeship	8349
11	Northumberland	Other qualifications	32548
12	Northumberland	Level 4 qualifications or above	52321
13	Northumberland	Other qualifications	1906
14	North Northamptonshire	No qualifications	19048
15	North Northamptonshire	Other qualifications	20148
16	North Northamptonshire	Other qualifications	27306
17	North Northamptonshire	Apprenticeship	10441
18	North Northamptonshire	Other qualifications	35858
19	North Northamptonshire	Level 4 qualifications or above	57404
20	North Northamptonshire	Other qualifications	4482
21	Birmingham	No qualifications	51860
22	Birmingham	Other qualifications	39489
23	Birmingham	Other qualifications	50221
24	Birmingham	Apprenticeship	15585
25	Birmingham	Other qualifications	73407
26	Birmingham	Level 4 qualifications or above	180826
27	Birmingham	Other qualifications	10082
28	Cambridgeshire	No qualifications	24125
29	Cambridgeshire	Other qualifications	27012
30	Cambridgeshire	Other qualifications	37974
31	Cambridgeshire	Apprenticeship	14593
32	Cambridgeshire	Other qualifications	57412
33	Cambridgeshire	Level 4 qualifications or above	158494
34	Cambridgeshire	Other qualifications	6200

In [33]:
```
Mert = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Merton']
Rich = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Richmond upon Tham
Wand = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Wandsworth']

Top5rt = pd.concat([Mert, Rich, Wand], ignore_index=True)
Top5rt
```

Out[33]:

	2022 local authorities: county	Qualification Type	Total
0	Merton	No qualifications	8956
1	Merton	Other qualifications	6526
2	Merton	Other qualifications	7942
3	Merton	Apprenticeship	3309
4	Merton	Other qualifications	13453
5	Merton	Level 4 qualifications or above	66101
6	Merton	Other qualifications	2925
7	Richmond upon Thames	No qualifications	3751
8	Richmond upon Thames	Other qualifications	3523
9	Richmond upon Thames	Other qualifications	5500
10	Richmond upon Thames	Apprenticeship	1804
11	Richmond upon Thames	Other qualifications	10829
12	Richmond upon Thames	Level 4 qualifications or above	68908
13	Richmond upon Thames	Other qualifications	1409
14	Wandsworth	No qualifications	8538
15	Wandsworth	Other qualifications	5933
16	Wandsworth	Other qualifications	8431
17	Wandsworth	Apprenticeship	2985
18	Wandsworth	Other qualifications	17872
19	Wandsworth	Level 4 qualifications or above	139034
20	Wandsworth	Other qualifications	3431

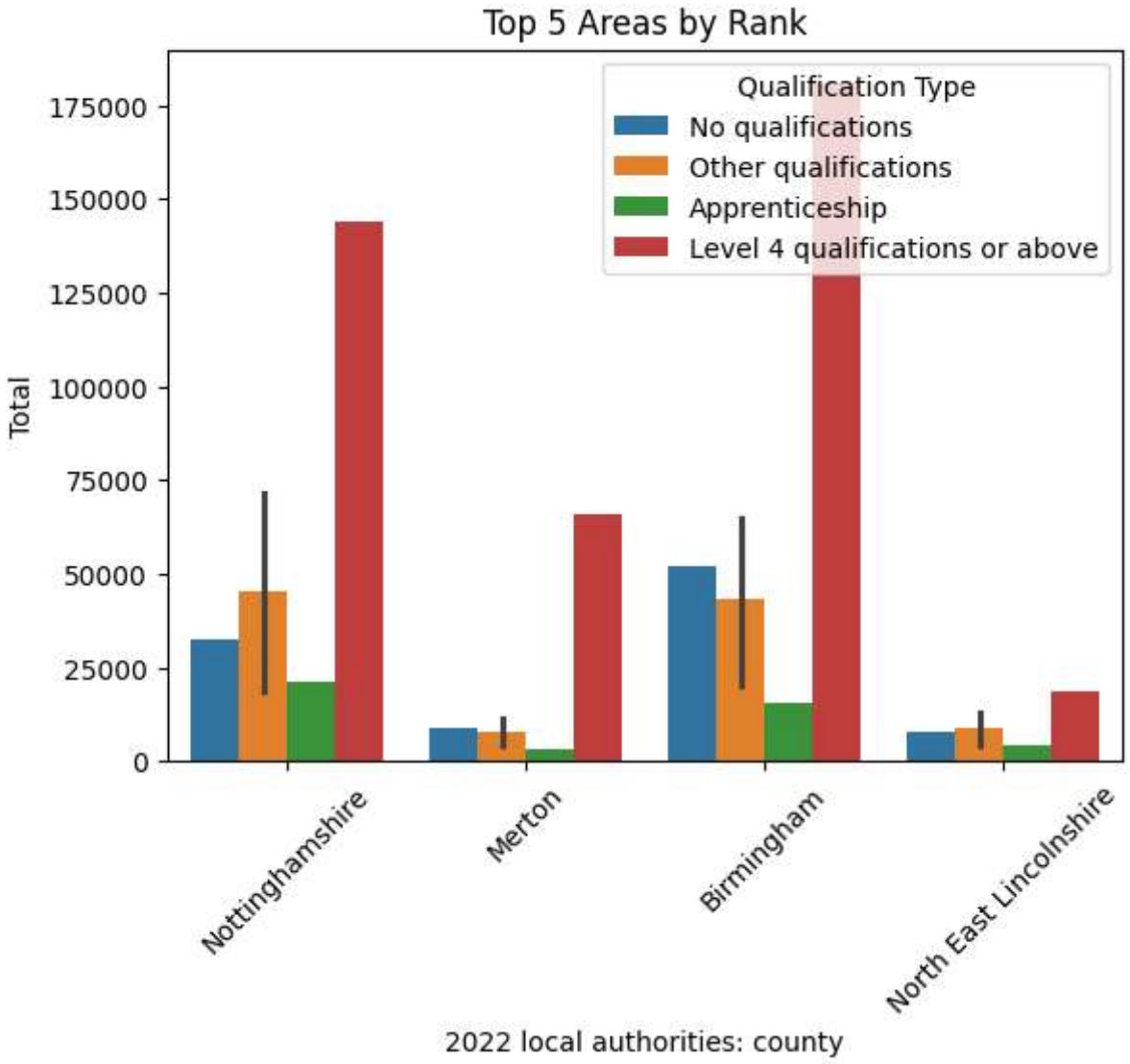
In [34]:
```
Nland = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Northumberland']
Norf = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Norfolk']
Ess = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Essex']
Linc = AreaQuali[AreaQuali['2022 local authorities: county'] == 'Lincolnshire']

Bottom5rt = pd.concat([Nland, Norf, Ess, Linc], ignore_index=True)
Bottom5rt
```

Out[34]:

	2022 local authorities: county	Qualification Type	Total
0	Northumberland	No qualifications	9939
1	Northumberland	Other qualifications	12398
2	Northumberland	Other qualifications	20706
3	Northumberland	Apprenticeship	8349
4	Northumberland	Other qualifications	32548
5	Northumberland	Level 4 qualifications or above	52321
6	Northumberland	Other qualifications	1906
7	Norfolk	No qualifications	39678
8	Norfolk	Other qualifications	44773
9	Norfolk	Other qualifications	63952
10	Norfolk	Apprenticeship	23836
11	Norfolk	Other qualifications	87385
12	Norfolk	Level 4 qualifications or above	135372
13	Norfolk	Other qualifications	8544
14	Essex	No qualifications	60591
15	Essex	Other qualifications	77586
16	Essex	Other qualifications	113671
17	Essex	Apprenticeship	36082
18	Essex	Other qualifications	150678
19	Essex	Level 4 qualifications or above	245544
20	Essex	Other qualifications	13546
21	Lincolnshire	No qualifications	35024
22	Lincolnshire	Other qualifications	36001
23	Lincolnshire	Other qualifications	51953
24	Lincolnshire	Apprenticeship	20577
25	Lincolnshire	Other qualifications	76817
26	Lincolnshire	Level 4 qualifications or above	110851
27	Lincolnshire	Other qualifications	8224

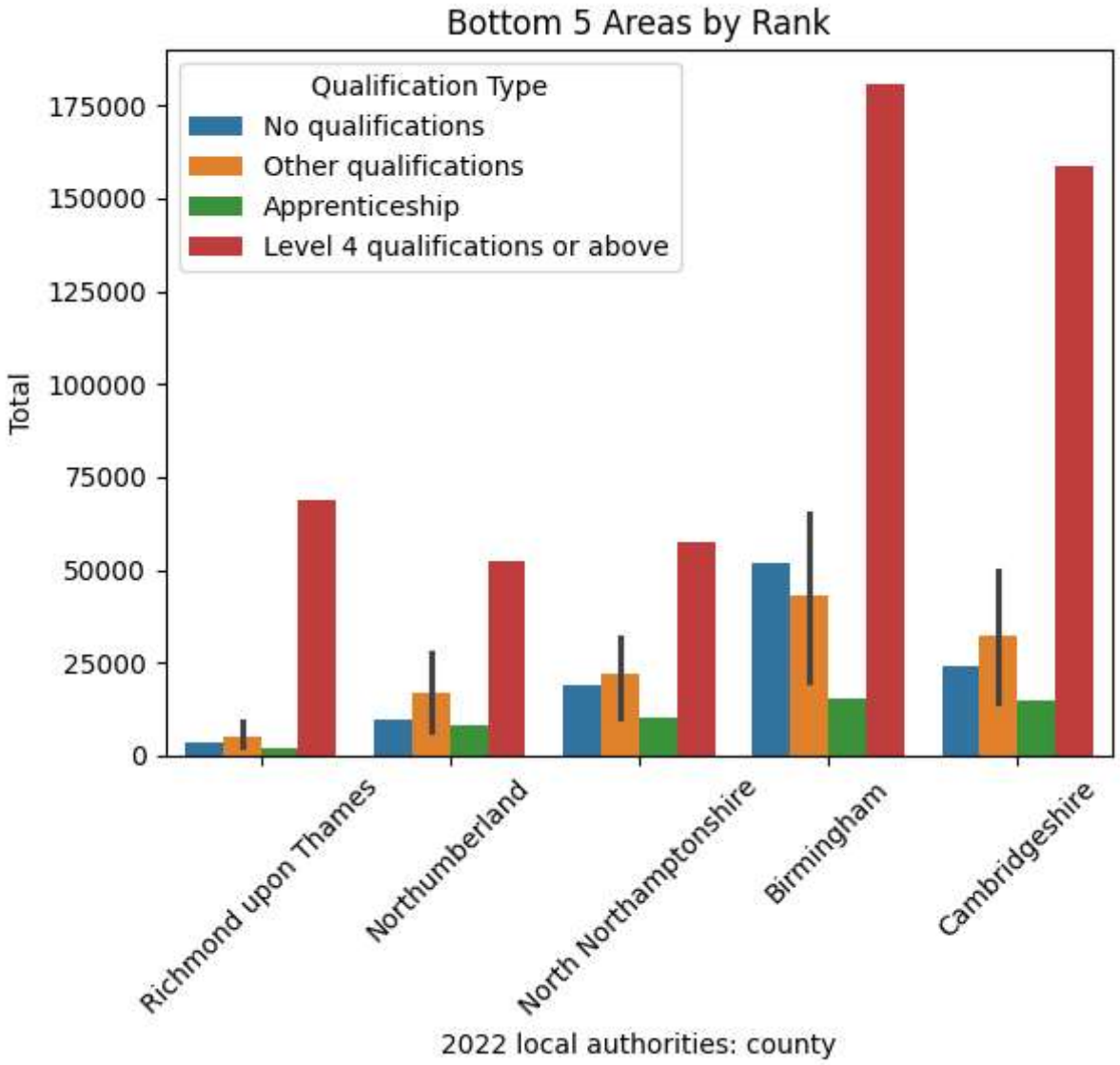
In [35]:
```
sns.barplot(data=Top5rn, x='2022 local authorities: county', y='Total', hue='Qualif
plt.xticks(rotation=45)
```

Out[35]:
```
([0, 1, 2, 3],
 [Text(0, 0, 'Nottinghamshire'),
  Text(1, 0, 'Merton'),
  Text(2, 0, 'Birmingham'),
  Text(3, 0, 'North East Lincolnshire')])
```



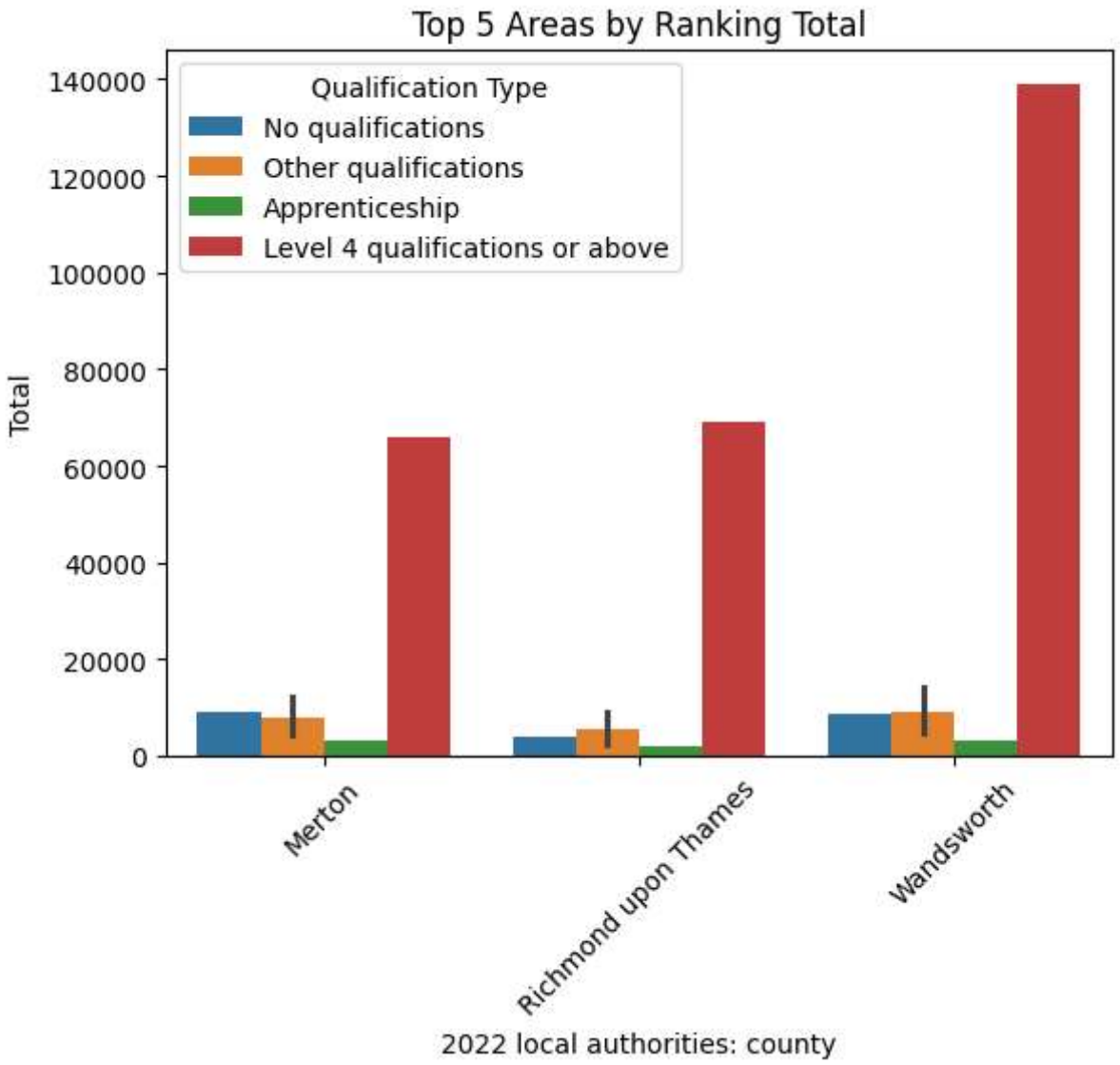
In [36]:
```
sns.barplot(data=Bottom5rn, x='2022 local authorities: county', y='Total', hue='Qua
plt.xticks(rotation=45)
```

Out[36]:
```
([0, 1, 2, 3, 4],
 [Text(0, 0, 'Richmond upon Thames'),
  Text(1, 0, 'Northumberland'),
  Text(2, 0, 'North Northamptonshire'),
  Text(3, 0, 'Birmingham'),
  Text(4, 0, 'Cambridgeshire')])
```



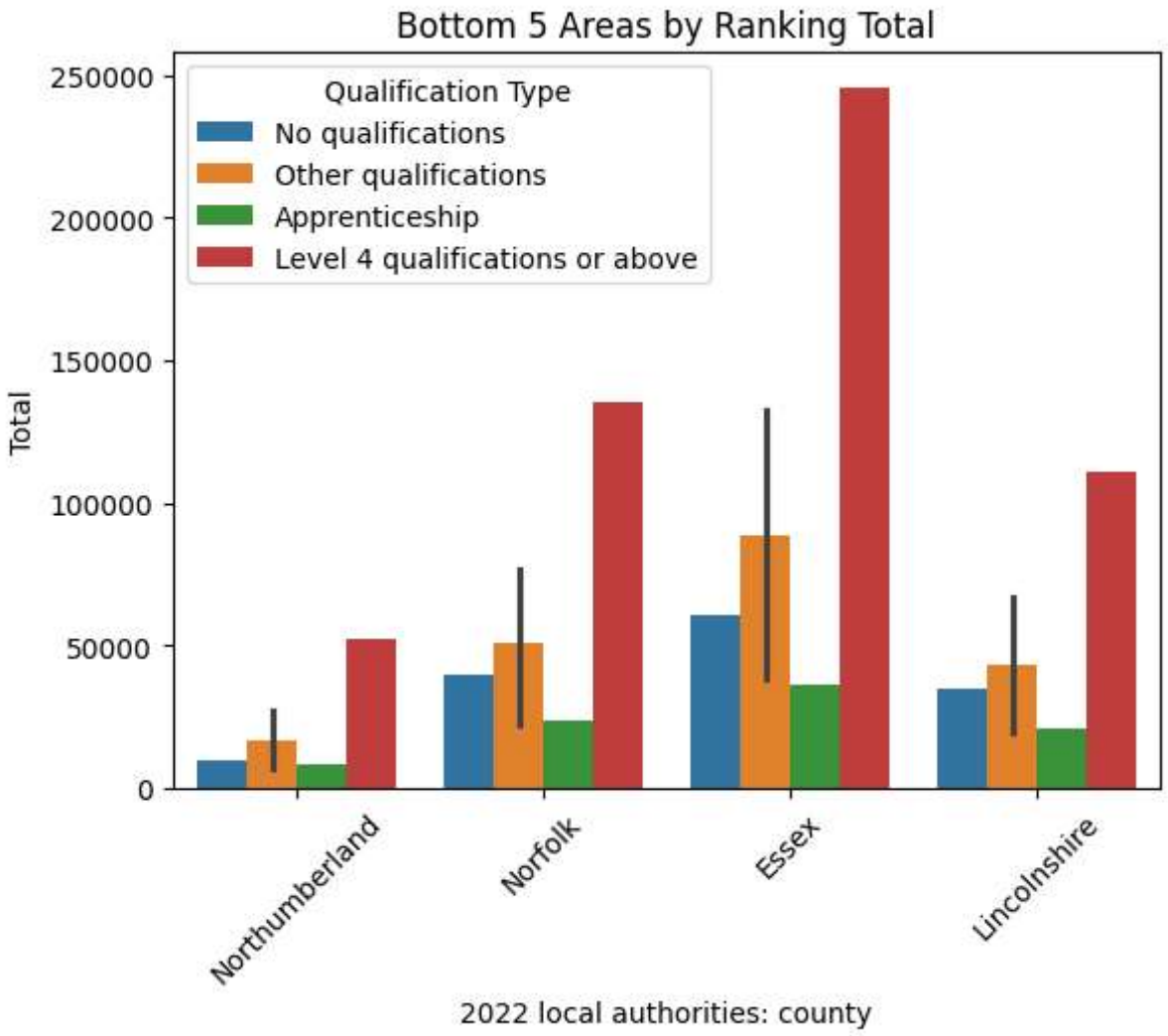
In [37]:
```
sns.barplot(data=Top5rt, x='2022 local authorities: county', y='Total', hue='Qualif
plt.xticks(rotation=45)
```

Out[37]:
```
([0, 1, 2],
 [Text(0, 0, 'Merton'),
  Text(1, 0, 'Richmond upon Thames'),
  Text(2, 0, 'Wandsworth')])
```



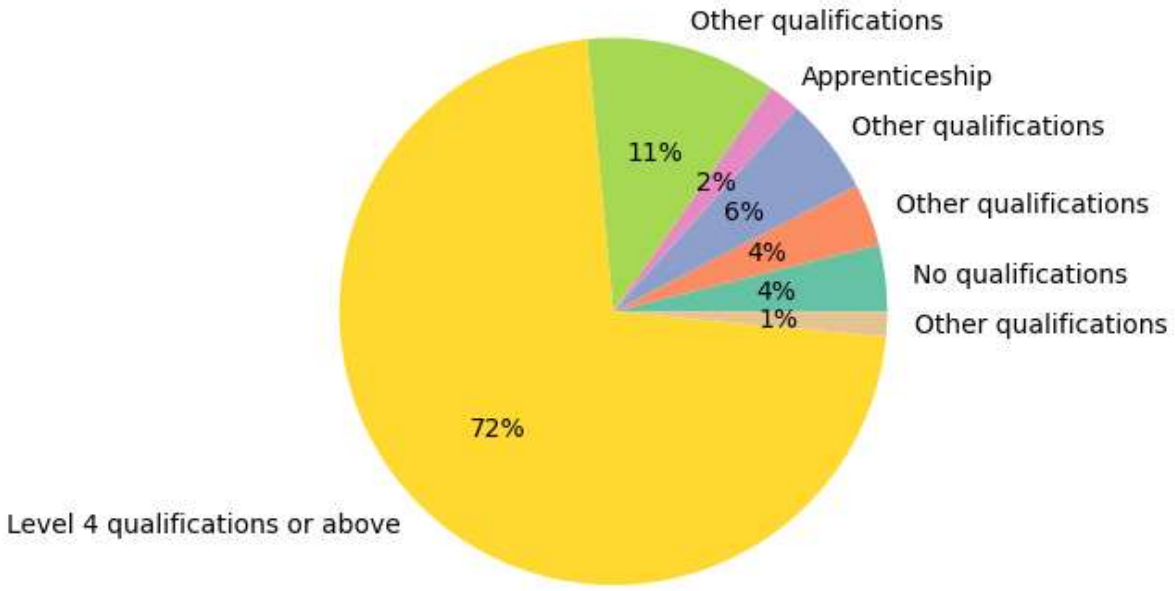
In [38]:
```
sns.barplot(data=Bottom5rt, x='2022 local authorities: county', y='Total', hue='Qua
plt.xticks(rotation=45)
```

Out[38]:
```
([0, 1, 2, 3],
 [Text(0, 0, 'Northumberland'),
  Text(1, 0, 'Norfolk'),
  Text(2, 0, 'Essex'),
  Text(3, 0, 'Lincolnshire')])
```



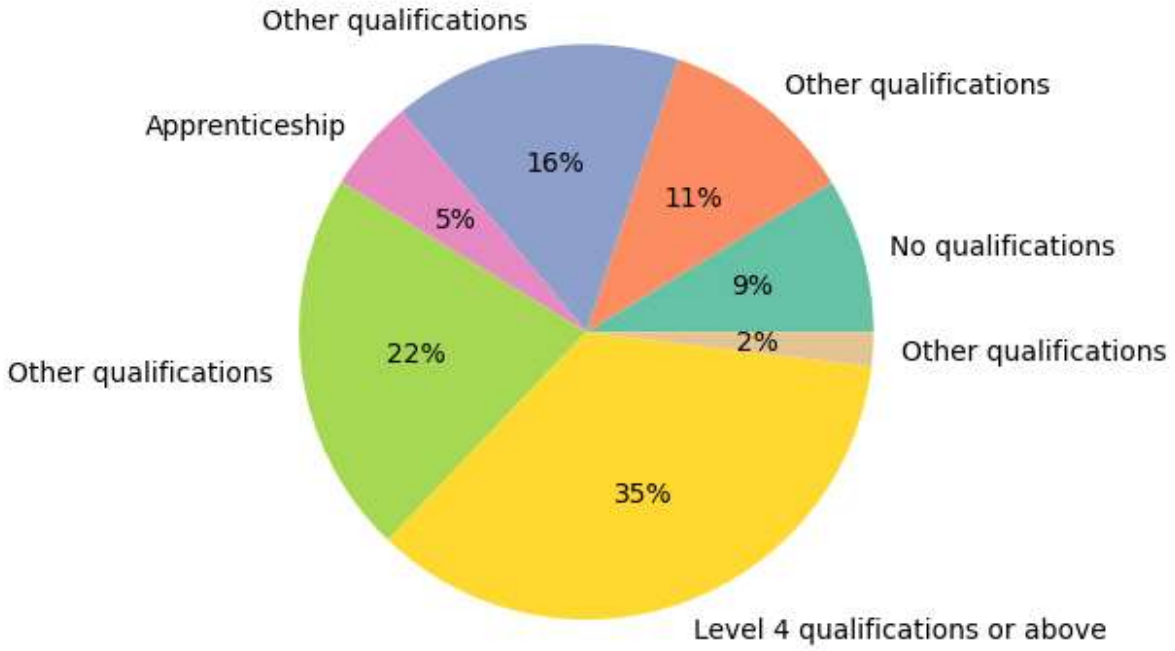
In [46]:
```
dataR = Rich['Total']
labelR = Rich['Qualification Type']
col = sns.color_palette("Set2")
plt.pie(dataR, labels=labelR, colors=col, autopct='%.0f%%')
```

Out[46]:
```
([<matplotlib.patches.Wedge at 0x7b47e257eb90>,
  <matplotlib.patches.Wedge at 0x7b47e257eaa0>,
  <matplotlib.patches.Wedge at 0x7b47e257f880>,
  <matplotlib.patches.Wedge at 0x7b47e252c130>,
  <matplotlib.patches.Wedge at 0x7b47e252d1e0>,
  <matplotlib.patches.Wedge at 0x7b47e251ab00>,
  <matplotlib.patches.Wedge at 0x7b47e251bf10>],
 [Text(1.0916753426690178, 0.13507385464434904, 'No qualifications'),
  Text(1.0287746609415476, 0.3893875922581562, 'Other qualifications'),
  Text(0.8703648742507359, 0.6726551759040443, 'Other qualifications'),
  Text(0.6857742689113936, 0.860066074263509, 'Apprenticeship'),
  Text(0.2812123282408972, 1.0634470491967778, 'Other qualifications'),
  Text(-0.7761052598844074, -0.7795258979532089, 'Level 4 qualifications or abov
e'),
  Text(1.0988241127644949, -0.05084849267501453, 'Other qualifications')],
 [Text(0.5954592778194642, 0.07367664798782675, '4%'),
  Text(0.5611498150590258, 0.2123932321408125, '4%'),
  Text(0.47474447686403776, 0.36690282322038775, '6%'),
  Text(0.3740586921334874, 0.4691269495982776, '2%'),
  Text(0.153388542676853, 0.5800620268346061, '11%'),
  Text(-0.42333014175513123, -0.4251959443381139, '72%'),
  Text(0.5993586069624517, -0.027735541459098834, '1%')])
```



In [48]:
```
dataE = Ess['Total']
labelE = Ess['Qualification Type']
plt.pie(dataE, labels=labelE, colors=col, autopct='%.0f%%')
```

Out[48]:
```
([<matplotlib.patches.Wedge at 0x7b47e2194cd0>,
  <matplotlib.patches.Wedge at 0x7b47e2194be0>,
  <matplotlib.patches.Wedge at 0x7b47e21959c0>,
  <matplotlib.patches.Wedge at 0x7b47e2196050>,
  <matplotlib.patches.Wedge at 0x7b47e21966e0>,
  <matplotlib.patches.Wedge at 0x7b47e2196d70>,
  <matplotlib.patches.Wedge at 0x7b47e2197400>],
 [Text(1.0593137095625744, 0.2964025383372714, 'No qualifications'),
  Text(0.6880604047755358, 0.8582382416206622, 'Other qualifications'),
  Text(-0.20278144094891595, 1.0811473938398415, 'Other qualifications'),
  Text(-0.8334219679808669, 0.7179190924379287, 'Apprenticeship'),
  Text(-1.090737938256875, -0.14244560381823593, 'Other qualifications'),
  Text(0.3701230481473663, -1.035861443065675, 'Level 4 qualifications or above'),
  Text(1.0979544221532263, -0.06705286626368218, 'Other qualifications')],
 [Text(0.5778074779432224, 0.16167411182032987, '9%'),
  Text(0.37530567533211034, 0.4681299499749066, '11%'),
  Text(-0.11060805869940869, 0.5897167602762772, '16%'),
  Text(-0.4545938007168364, 0.3915922322388702, '5%'),
  Text(-0.5949479663219317, -0.07769760208267414, '22%'),
  Text(0.2018852989894725, -0.5650153325812772, '35%'),
  Text(0.5988842302653961, -0.03657429068928118, '2%')])
```



In [ ]:
```
Activity_mapping = {"Employed": 4, "Further Study": 3, "Mixture": 2, "No employment
GradData['Activity'] = GradData['Activity'].map(Activity_mapping)

MoFS_mapping = {"Full-time": 3, "Part-time": 2, "All": 1}
GradData['Mode of former study'] = GradData['Mode of former study'].map(MoFS_mappir

LoQO_mapping = {"Postgraduate": 3, "Undergradute": 2, "All": 1}
GradData['Level of qualification obtained'] = GradData['Level of qualification obta
```

In [ ]:
```
GradData = GradData.drop(['Provider name'], axis = 1)
```

In [ ]:
```
from sklearn.model_selection import train_test_split

predictors = GradData.drop(['Level of qualification obtained', 'Activity'], axis =
target = GradData["Total"]
x_train, x_val, y_train, y_val = train_test_split(predictors, target, test_size = 0
```

In [ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score

logreg = LogisticRegression()                                #Store The Model In My C
logreg.fit(x_train, y_train)                                 #Train The Model With Th
y_pred = logreg.predict(x_val)                               #Predict The Values Of T
acc_logreg = round(accuracy_score(y_pred, y_val) * 100, 2) #Compare The Predicted V
print(acc_logreg)
```

```
70.48
```

In [ ]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score

dt = DecisionTreeClassifier()                              #Store The Model In My Own V
dt.fit(x_train, y_train)                                   #Train The Model With The Tr
y_pred = dt.predict(x_val)                                 #Predict The Values Of The V
acc_dt = round(accuracy_score(y_pred, y_val) * 100, 2) #Compare The Predicted Value
print(acc_dt)
```

```
99.98
```

In [ ]:
```
from sklearn.ensemble import RandomForestClassifier

randf = RandomForestClassifier()                          #Store The Model In My Ow
randf.fit(x_train, y_train)                               #Train The Model With The
y_pred = randf.predict(x_val)                             #Predict The Values Of Th
acc_randf = round(accuracy_score(y_pred, y_val) * 100, 2) #Compare The Predicted Va
print(acc_randf)
```

```
99.95
```

In [ ]:
```
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()                            #Store The Model In My Own
knn.fit(x_train, y_train)                               #Train The Model With The T
y_pred = knn.predict(x_val)                             #Predict The Values Of The
acc_knn = round(accuracy_score(y_pred, y_val) * 100, 2)  #Compare The Predicted Val
print(acc_knn)
```

```
99.94
```

In [ ]:
```
models = pd.DataFrame({
    'Model': ['Logistical Regression', 'Decission Tree', 'Randon Forest', 'KNN'],
    'Score': [acc_logreg, acc_dt, acc_randf, acc_knn]})
models.sort_values(by = 'Score', ascending = False)
```

Out[ ]:

	Model	Score
1	Decission Tree	99.98
2	Randon Forest	99.95
3	KNN	99.94
0	Logistical Regression	70.48