A Study on Mental Health Conditions and Employment Rates in London

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Abstract

Mental illness is usually treated with great disdain in the workplace causing unfriendly working environment and unemployment among people suffering or diagnosed with previous mental disorders. The aim of the study was to explore the association between the mental health conditions and the employment rates in the city of London. Using descriptive statistics and cluster analysis, we can explore the various datasets. Through regression analysis, a significant relationship between various mental illnesses and employment can be found.

1 INTRODUCTION

In the recent years, there has been a wide acknowledgement of the illnesses that go beyond just physical. Mental illness has always played a role in the day-to-day activities of our lives. However, it was not recognised as a valid reason until recently. Problems like depression, anxiety, bipolar disorder, obsessive compulsive disorder, any phobias and so on are only now acknowledged for the serious threat it posed to the well-being of human beings and sometimes, even lives. Mental illnesses can cause physical ailments which can be fatal. Severe mental health problems can cause manic episodes that can threaten a person's life and the people around. It affects everyone, regardless of age, gender, economic status and so on.

Mental health is often used incorrectly as a reason for everyday problems. It was once portrayed as a way to lead people to religious myths. It encouraged the hope of accomplishing particularly hard problems in life by believing or following substitute means i.e. religious beliefs (Szasz, 1960). With global awareness programs, this stigma is slowly fading. However, the number of people who suffer from mental illness is increasing drastically. Not all mental illnesses can be treated but there have been substantial advancements in the field. Chronic mental disorders like schizophrenia and dementia have no cure. However, they can be kept in check and controlled, so as to not turn fatal. All physical ailments caused by mental health are treatable. Mental illness does not affect the mind and body alone but it interferes with the daily workings of life. Many people suffering from any kind of mental illness are reported to have less focus, less productivity and motivation and so on (Burton, Schultz, Chen, & Edington, 2008). Depression is the predominant reason for disability. Mental disorders play a major role in the worldwide disability burden. Economic burden is also effected by the various mental disorders.

When an employee has a mental health condition, they experience something known as presenteeism. Presenteeism refers to the lack of productivity of an employee when they are present at their job because of a mental illness. People with poor mental health are less likely to be employed. In 2004, the United Kingdom recorded that 74 percent of the population within the working age range was employed but 21 percent were considered disabled due to previous mental illness problems (Force, 2006). A study in Sweden aimed at the link between psychiatric problems and unemployment reported an additional 10 days of unemployment annually for people diagnosed with a psychiatric condition (Mousteri, Daly, Delaney, Tynelius, & Rasmussen, 2019).

2 LITERATURE REVIEW

Mental disorders cause character defects and hindrances that greatly affect the ability to work such as poor social skills, unorganised thought process, lack of logical reasoning, paranoid delusions and so on (Baron & Salzer, 2002). The paper mentions a few cases where mental health conditions have hindered with people's professional lives. It quotes a college graduate who found that he lacked the cognitive ability to run a cash register and a nurse who experienced paranoia which cost her any relationship with her co-workers. There are people who have been fired for substantial mistakes caused due to their mental health. Most symptoms of these disorders prevent individuals from doing their jobs. People with mental illness have the same working pattern as those who do not have a mental illness i.e. the kind of jobs and hours of work remain the same. The mental illness affects the cognitive ability for simple tasks. This decreases the productivity of employees with mental illness. It also discourages people from attempting to acquire a job due to the lack of confidence.

A study reported five percent higher absence rates from jobs among employees with a history of one or more mental illnesses (Bubonya, Cobb-Clark, & Wooden, 2017). The poor mental health of the workers take a toll on the productivity of their jobs which in turn is a significant economic cost on the companies, its workers and the society. As a result of emotional stress or problems, employees with poor mental health are reported to have diminished working capacity up to six times less than employees with stable or good mental health conditions. Another study conducted presents a series of regression models that explores the relationship between mental health and future employment prospects (Butterworth, Leach, Pirkis, & Kelaher, 2012). Initial analysis showed a significant association between unemployment and mental health for men and women. Lower mental stability (or poor mental health) were followed by longer periods of unemployment. The results from the model states that men with poor mental health experience 5.1 weeks of unemployment in the following 4 years and women with poor mental health experience 6.7 weeks of unemployment in the following 4 years.

There has been significant work that study the cause and effect of unemployment and mental disorders. By eliminating the risk of reverse causality, another study (Bubonya, Cobb-Clark, & Ribar, 2019) explores the effect of mental health and employment in one period on a following period. The findings of this study states that severe depressive symptoms is followed by an increase in unemployment rates by 34.2 percent for men. However, it did not yield any significant results for women. There is little to no evidence for the effect of poor employment structures and patterns on mental disorder symptoms. A study conducted in the US in 2009-10 aimed at the state of employment as a result of the severity of mental health (Luciano & Meara, 2014). After controlling for substance use disorders, logistic regression was used to conclude that with high severity of mental illness, the employment rates decreased. With no mental illness, the model recorded 75.9 percent of employment whereas with serious mental illness, it recorded 54.4 percent of employment. For people under the age of 50, the relationship between mental illness and employment was much weaker than for people above the age of 50.

There have also been numerous studies that show the opposite relationship which shows the depressive symptoms among unemployed population. A study conducted in Korea resulted that depressive episodes were the most common trait among the unemployed group and the least prevalent in the employed group in their study population (Yoo et al., 2016). The likelihood of having depressive symptoms was high in the people who had a worse employment status than those who are permanently employment. Unemployment is followed by reduction in psychological well-being with a greater chance of depressive and anxiety symptoms (Wilson & Walker, 1993). There are debates that have lasted decades about which one precedes the other. It is not very certain which indicator is the predictor.

3 DATA

The data used in this study was collected by various national sources compiled in the London DataStore under the Employment and Health topics (*london*, n.d.). The website allows to view and use free data about London regarding environment, demographics, transport and so on collected from various national open sources.

3.1 Qualifications by Economic Status, Borough

The dataset contains the number of people that are employed in different National Vocational Qualifications from 2004 to 2019. An NVQ is a job-oriented qualification levels for learning in institutions and companies. Entry level is ideal for people with little to no technical knowledge or previous experience. NVQ Level 1 employment which covers the introduction to the department and practical application of basic education. NVQ Level 2 is ideal for employees with complex technical duties. NVQ Level 3 is ideal for people capable of more responsibility under guidance. NVQ Level 4 is an in-dept learning of technical knowledge and experience for a specific area of expertise. The dataset was originally collected by the Office for National Statistics. It covers people in London by each borough and general area along with the countries that comprise the United Kingdom. The economically active population has been grouped into various NVQs including Trade Apprenticeships, other and no qualifications. The data is also divided for working population age, working age males and working age females comprising of the number and percentage.

3.2 London's Job History

The dataset contains employment rates relating to each borough in London along with the total in the entire city from 1984 to 2010 collected originally by Office for National Statistics. It was created 10 years ago and updated 3 years ago. It consists only of employee jobs. The dataset consists of full-time, part-time and second jobs among the employed population of London. It is counted from business surveys which do not include working proprietors paid through the PAYE system which collects Income tax and insurance from employment.

3.3 Prevalence of Common Mental Health Problems, Borough

The dataset was originally collected by the Public Health England which consists of the number of cases of the most common mental health conditions like neurotic disorders, phobias, anxiety and depression. for people from the ages of 16 to 74 years as a rate of 1000 per population divided by each borough and different areas of London. It also contains estimated cases for each kind of the common mental illnesses along with the working age population in each borough and area.

4 HYPOTHESIS

Various mental health issues have a significant impact on the capability of a person to work. Either, due to the inability to participate and find something interesting, one might lack the motivation and/or ability to work or, due to high levels of endorphins produced, a person can become overly active thereby increasing productivity and efficiency.

(a) There may be correlations among the various mental health conditions in the boroughs of London

(b) The presence of mental health conditions may affect the employment rates

(c) The employment qualifications or positions may be dependent on mental health conditions

5 DATA CLEANING

The employment and qualification datasets consists of data from various years. However, the dataset regarding mental health consisted of data only from 2006. Hence, the first two datasets have to be filtered to contain data points only from 2006. Using Python and Excel, the values for 2006 were extracted into a csv file for further cleaning and analysis. The London's job history dataset contains information about the total employment rate in all of London too. The economically active population qualification specific dataset contains data points grouped by areas in London apart from the boroughs along with the data for the countries of the United Kingdom. Since this study is borough specific, this information is irrelevant.

The qualification dataset has the number of economically active population, the denominator, the percentage and the confidence level for each qualification and borough. In the study, only the number in each qualification levels are important. The mental health dataset contains estimated values for the different mental health conditions which are not relevant to this study. The dataset that explore the economically active population by their qualification levels had a few missing data points. The values for the City of London were available for NVQ4+ qualifications. However, the data for the other qualifications were missing. Since the rest of the data for each borough and qualification were plenty, these values are omitted from the analysis using the pandas package in Python.

The borough specific data for London's job history from 1984 to 2010 and the prevalence of common mental health problems did not have any missing values. The datasets have the necessary and sufficient data to conduct the analysis. Using regression analysis, we can explore the association between mental health conditions and employment rate in the boroughs of London. To do the analysis, we use Python to merge the datasets that contain the prevalence of mental health in all London boroughs and the employment rates in 2006 from the London's job history. Since the boroughs are the same for both datasets, it is easy to merge the filtered datasets to complete the analysis. We can also find the relationship between the qualifications of employment and the mental health conditions in London. We can easily merge the corresponding datasets to find the correlation among these indicators by the borough.

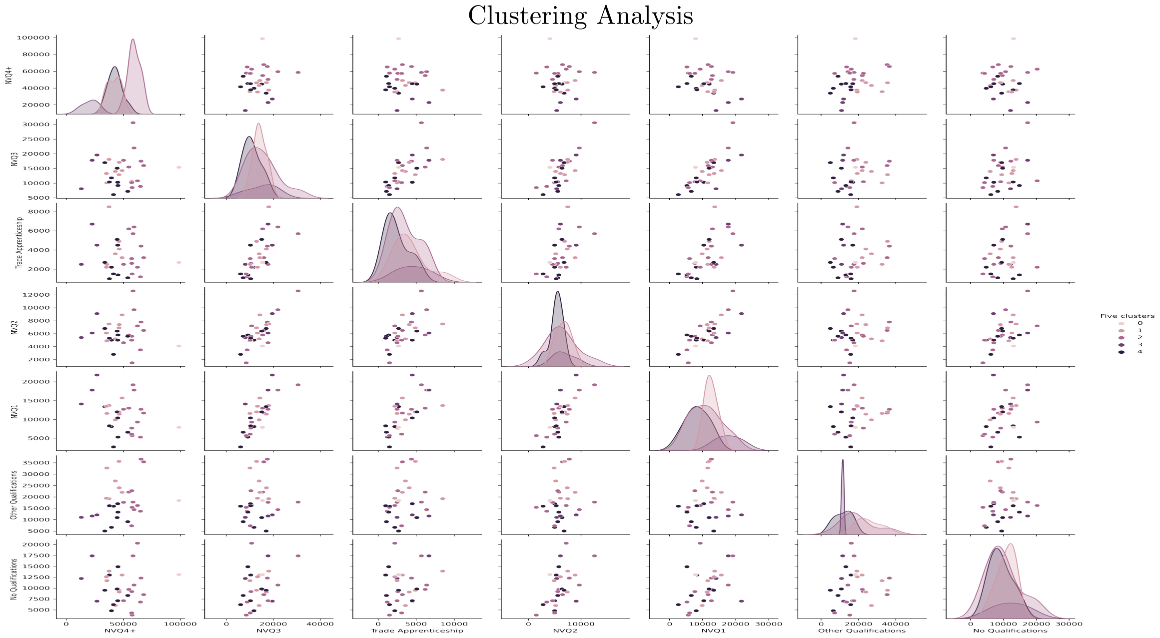

Figure 1: K-means clustering with 5 clusters for the various employment classifications

6 DATA ANALYSIS

While exploring the data regarding the qualifications with different scatter plots, there were some diversity in the data that could be seen. There were clearly some groupings among the data that could be found. Cluster analysis is a method used to group data points that have some similar characteristics. Identifying similar traits help further analysis of the different qualifications for employment in London. Cluster analysis was performed on the data to find the various groupings for the different qualifications. Using k-means clustering in Weka, the 30 different boroughs in London were grouped into 5 clusters with a split of 63 percent in cluster 0, 7 percent in cluster 2 and 10 percent in clusters 1, 3 and 4. The centroids for each cluster are:
Cluster 0 <– Barnet
Cluster 1 <– Brent
Cluster 2 <– Hammersmith and Fulham
Cluster 3 <– Barking and Dagenham
Cluster 4 <– Bexley

Figure 1 visualises the the clusters formed using seaborn and sklearn packages in Python. In each graph, the clustered points approximately represent different parts of London. The geographical location plays an important part in the qualification of employment.

Exploring the London's job history by borough, it is seen that in 2006, the City of London has the highest employment rate among the boroughs with over 300 per thousand employees. However, the data for the other indicators are not available for City of London. Hence, this borough cannot be considered. With around 250 per thousand employees, Camden follows behind and Tower Hamlets with around 200. Barking and Dagenham has the least employment rate of 50 per thousand employees. Figure 2 shows the distribution of employment rates for the various boroughs of London.

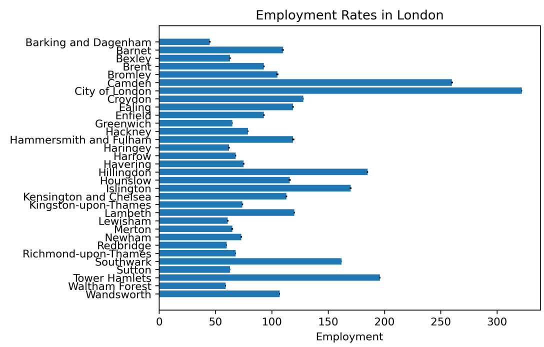

Figure 2: Distribution of employment rates across all boroughs in London in 2006

The prevalence of common mental health problems shows the number of people in each borough that has a certain mental health condition. The prevalence of any neurotic disorder are higher than the other conditions. While Islington has the most number of people with neurotic disorders, mixed anxiety and depression, and obsessive compulsive disorder with 212.7, 100 and 18.7 per 1000 population, Hackney has the most number of people with any phobias with 25.9 per

	Any neurotic disorder	All phobias	Depression	Anxiety disorder	Anxiety & Depression	OCD	Panic disorder
Any neurotic disorder	1.000000	0.996714	0.987011	0.976751	0.995575	0.995764	0.990136
All phobias	0.996714	1.000000	0.975665	0.964296	0.996846	0.994086	0.978497
Depression	0.987011	0.975665	1.000000	0.995894	0.968177	0.977514	0.994176
Anxiety disorder	0.976751	0.964296	0.995894	1.000000	0.953151	0.959982	0.991584
Anxiety & Depression	0.995575	0.996846	0.968177	0.953151	1.000000	0.995036	0.975093
OCD	0.995764	0.994086	0.977514	0.959982	0.995036	1.000000	0.978410
Panic disorder	0.990136	0.978497	0.994176	0.991584	0.975093	0.978410	1.000000

Table 1: Correlation Coefficients among the different kinds of mental health conditions in the boroughs of London

1000 population. Lambeth has the most with depressive episodes, generalised anxiety disorder and panic disorder with 40.6, 62.3 and 9.8 per 1000 population.

The odds of suffering from a mental health disorder is relatively high if you already have another disorder. The chance of a person having more than one mental health condition is also very high. The symptoms of many of these conditions are similar and the prevalence of one can lead to the existence of another. Table 1 shows the different correlation coefficients for the different mental health conditions using Python. From the table, it is seen that, there is a strong positive relationship between all the conditions.

$$r = \frac{\sum(x_i - \bar{x})(y_i - \bar{y})}{\sum(x_i - \bar{x})\sum(y_i - \bar{y})}$$

The above formula gives the correlation coefficient of between variables.

Using multiple regression, we can explore how employment rate in London is affected by the prevalence of various mental health disorders. Not all conditions will have the same effect on the employment rates. Through the regression analysis, we can find the conditions that have a role in the employment rates of London and to what extent. The regression model for multiple variables is given by

$$y = a_0 + a_1x_1 + a_2x_2 + ...$$

Table 2 shows three different regression models that can be used based on the significance of each of the independent variables using JASP. It includes the coefficients, the standard error and the p-value for all the conditions in all three models. The first model shows the effect on employment rates while considering all the conditions. It is seen that for depressive episodes, $p = .591$ which implies that it does not have a significant impact on the employment rates. Hence, in the second model, we eliminate depressive episodes from the analysis. In the next model, panic disorder has a value of $p = .396$ which implies that it does not effect the employment rates in London to a great extent. Hence, in the third and final model, we eliminate panic disorder from the analysis. In the final model, we can see that $p < .05$ for all the remaining variables which have a significant effect on the employment rates in London.

The multiple regression model is given by

$$ER = -65.076 - 96.245(ND) - 270.423(P) + 126.745(AD) + 145.273(MAD) + 297.895(OCD)$$

where
ER represents the employment rate
ND represents neurotic disorders
P represents all phobias
AD represents anxiety disorders
MAD represents mixed anxiety and depression
and OCD represents obsessive compulsive disorders

When there is no change in the independent variables, the employment rate would be at -65.076 which indicates a total inverse relationship between the employment rate and all the conditions considered in the third model. When neurotic disorders and phobias increase by a unit, employment rate decreases by 96.245 units and 270.423 units respectively. When anxiety disorder, mixed anxiety and depression and obsessive compulsive disorder increase by a unit, the employment rate also increases by 126.745 units, 145.273 units and 297.895 units respectively.

From the model, we can see that there is an inverse relationship between the employment rate and neurotic disorders and phobias. However, there is a direct relationship between employment rate and anxiety disorders, mixed anxiety and depression and obsessive compulsive disorder as seen in figure 3.

It is important to note that the interaction effect between the independent variables i.e the mental

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
1	(Intercept)	40.407	168.530		0.240	0.813
	Any neurotic disorder-Rates per 1000 population	−137.940	66.016	−42.736	−2.090	0.048
	All phobias-Rates per 1000 population	−251.254	67.665	−9.877	−3.713	0.001
	Depressive episode-Rates per 1000 population	−32.879	60.256	−1.856	−0.546	0.591
	Generalised anxiety disorder-Rates per 1000 population	169.693	68.519	14.506	2.477	0.021
	Mixed anxiety depression-Rates per 1000 population	179.488	66.046	27.130	2.718	0.013
	Obsessive compulsive disorder-Rates per 1000 population	423.630	170.106	11.831	2.490	0.021
	Panic disorder-Rates per 1000 population	131.457	164.566	1.783	0.799	0.433
2	(Intercept)	−0.831	148.316		−0.006	0.996
	Any neurotic disorder-Rates per 1000 population	−134.078	64.625	−41.539	−2.075	0.049
	All phobias-Rates per 1000 population	−235.878	60.572	−9.272	−3.894	< .001
	Generalised anxiety disorder-Rates per 1000 population	148.266	55.285	12.675	2.682	0.013
	Mixed anxiety depression-Rates per 1000 population	175.735	64.677	26.563	2.717	0.012
	Obsessive compulsive disorder-Rates per 1000 population	373.900	141.421	10.442	2.644	0.015
	Panic disorder-Rates per 1000 population	139.467	161.388	1.891	0.864	0.396
3	(Intercept)	−65.076	127.660		−0.510	0.615
	Any neurotic disorder-Rates per 1000 population	−96.245	47.286	−29.818	−2.035	0.053
	All phobias-Rates per 1000 population	−270.423	45.267	−10.630	−5.974	< .001
	Generalised anxiety disorder-Rates per 1000 population	126.745	49.098	10.835	2.581	0.016
	Mixed anxiety depression-Rates per 1000 population	145.273	53.940	21.959	2.693	0.013
	Obsessive compulsive disorder-Rates per 1000 population	297.895	110.160	8.319	2.704	0.012

Table 2: Multiple Regression models to explore the relationship between the employment rates and various mental health conditions in London

health conditions is not taken into consideration in the model. In table 1 we see the correlations amongst the variables. This correlation is ignored during multiple regression analysis as we hold all variables constant while finding the relationship between the dependent and one independent variable.

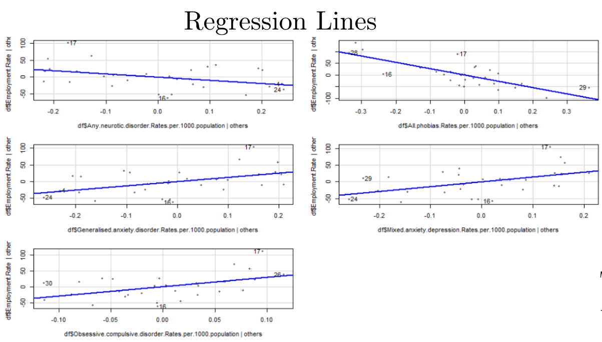

Figure 3: Positive and Negative Regression Lines between Employment Rates and Neurotic Disorder (first row left), Phobias (first row right), Generalised Anxiety Disorder (second row left), Mixed Anxiety and Depression (second row right) and Obsessive Compulsive Disorder (bottom left)

The p-value and the F-statistic together determine if the model is significant. A low p-value indicates that the model is significant. The F-statistic compares the model with the intercept model to test the significance of the model. The p-value for all three models were $< .001$ with the F-statistics for the first model being 8.194, the second model being 9.810 and the third model being 11.746 as seen in table 3. F-statistic is given by

$$F = \frac{\frac{SumOfSquares}{DegreesOfFreedom}}{\frac{ErrorSumOfSquares}{ErrorDegreesOfFreedom}}$$

ANOVA

Model		Sum of Squares	df	Mean Square	F	p
1	Regression	83643.528	7	11949.075	8.194	< .001
	Residual	32081.939	22	1458.270		
	Total	115725.467	29			
2	Regression	83209.354	6	13868.226	9.810	< .001
	Residual	32516.112	23	1413.744		
	Total	115725.467	29			
3	Regression	82153.591	5	16430.718	11.746	< .001
	Residual	33571.876	24	1398.828		
	Total	115725.467	29			

Table 3: ANOVA for all the three models of multiple regression analysis

The critical values for the three models are 2.46, 2.53 and 2.62 for the alpha level of .05 and 3.58, 3.71 and 3.89 for the alpha level of .01. Hence, we can conclude that all three models are significant. Table 4 shows the R, R^2, Adjusted R^2 and the root mean square deviation of all three models.

Model Summary - Employment Rate

					Durbin-Watson		
Model	R	R²	Adjusted R²	RMSE	Autocorrelation	Statistic	p
1	0.850	0.723	0.635	38.187	0.056	1.788	0.493
2	0.848	0.719	0.646	37.600	0.034	1.818	0.579
3	0.843	0.710	0.649	37.401	0.042	1.775	0.497

Table 4: Summary for all the three models of multiple regression analysis

Pearson's Correlations

Variable		NVQ4+	NVQ3	Trade Apprenticeship	NVQ2	NVQ1	Other Qualifications	No Qualifications
Any neurotic disorder-Rates per 1000	Pearson's r	0.343	-0.598	-0.648	-0.361	-0.623	-0.022	0.144
	p-value	0.064	< .001	< .001	0.05	< .001	0.91	0.447
All phobias-Rates per 1000 population	Pearson's r	0.349	-0.591	-0.643	-0.347	-0.615	-0.02	0.151
	p-value	0.059	< .001	< .001	0.06	< .001	0.914	0.425
Depressive episode-Rates per 1000	Pearson's r	0.332	-0.599	-0.642	-0.338	-0.621	-0.032	0.142
	p-value	0.073	< .001	< .001	0.068	< .001	0.869	0.453
Generalised anxiety disorder-Rates per 1000 population	Pearson's r	0.368	-0.586	-0.641	-0.333	-0.624	-0.033	0.133
	p-value	0.045	< .001	< .001	0.072	< .001	0.864	0.484
Mixed anxiety depression-Rates per 1000 population	Pearson's r	0.344	-0.595	-0.645	-0.369	-0.621	-0.027	0.145
	p-value	0.063	< .001	< .001	0.045	< .001	0.885	0.444
Obsessive compulsive disorder-Rates per 1000	Pearson's r	0.302	-0.608	-0.648	-0.358	-0.619	-0.014	0.16
	p-value	0.105	< .001	< .001	0.052	< .001	0.943	0.399
Panic disorder-Rates per 1000 population	Pearson's r	0.369	-0.611	-0.663	-0.392	-0.651	-0.012	0.11
	p-value	0.045	< .001	< .001	0.032	< .001	0.951	0.562

Table 5: Correlation coefficients between the Employment Qualifications and the Mental Health Disorders in London

We can also find the relationship between the mental health conditions and the qualifications for employment. From table 5, we can see that employees with NVQ4+ i.e. high qualifications, do not have a weak positive relationship with any of the mental health conditions. Employees with NVQ3 qualifications and trade apprenticeship have a moderately negative relationship with all the mental conditions. NVQ2, NVQ1 and other qualifications have a weak negative relationship. However, considering the p-values, we can say that employees with NVQ3, Trade Apprenticeship and NVQ1 are seen to have a significant effect due to the various mental health conditions.

7 CONCLUSIONS

7.1 Results

Neurotic disorders and all phobias have a significant effect on the employment rates in the different boroughs of London. Although the net total shows an indirect relationship between all mental conditions and the employment rates, a few of the conditions show a poor positive relationship. We can also find significant relationships between the mental health conditions and the employment qualifications from the datasets used.

7.2 Limitations

The datasets used in the study might be outdated. Due to lack of data available that could match the objectives of this study, the data used is from 2006. There have been significant improvement in employment levels and mental health conditions in the past decade or two. Hence, the results in this study may not be accurate to the current day and age. However, this does form a framework for future studies on similar objectives. The methodology and analysis used in this study can be replicated. Due to the missing data from the City of London, the results cannot be generalised to all parts of London.

During multiple regression analysis, the interaction between the independent variables were not considered. This may alter the resulting model. However, since the aim of this study was to find the different relationships between various mental health conditions and the employment rates, it does not deter too much from the true results.

Most of the data were not categorised to genders. Hence, there may occur less representation for the different genders. The age group considered for the health problems were from 16 to 74. There is a lack of representation to other age groups. The employment rates do not consider the self-employed population of London.

7.3 Further Studies

This study can be used a frame work for further analysis into the effect of mental health problems and the qualifications of employment. There has been adequate literature on the relationship between mental health and employment. However, mental health plays a role in the employment position and rank of employees which has not been explored too much.

References

(n.d.).

Baron, R. C., & Salzer, M. S. (2002). Accounting for unemployment among people with mental illness. *Behavioral sciences & the law*, *20*(6), 585–599.

Bubonya, M., Cobb-Clark, D. A., & Ribar, D. C. (2019). The reciprocal relationship between depressive symptoms and employment status. *Economics & Human Biology*, *35*, 96–106.

Bubonya, M., Cobb-Clark, D. A., & Wooden, M. (2017). Mental health and productivity at work: Does what you do matter? *Labour economics*, *46*, 150–165.

Burton, W. N., Schultz, A. B., Chen, C.-Y., & Edington, D. W. (2008). The association of worker productivity and mental health: a review of the literature. *International Journal of Workplace Health Management*.

Butterworth, P., Leach, L. S., Pirkis, J., & Kelaher, M. (2012). Poor mental health influences risk and duration of unemployment: a prospective study. *Social psychiatry and psychiatric epidemiology*, *47*(6), 1013–1021.

Force, S. E. T. (2006). *Reaching out: An action plan on social exclusion. hm government of the united kingdom.*

Luciano, A., & Meara, E. (2014). Employment status of people with mental illness: national survey data from 2009 and 2010. *Psychiatric Services*, *65*(10), 1201–1209.

Mousteri, V., Daly, M., Delaney, L., Tynelius, P., & Rasmussen, F. (2019). Adolescent mental health and unemployment over the lifespan: population evidence from sweden. *Social Science & Medicine*, *222*, 305–314.

Szasz, T. S. (1960). The myth of mental illness. *American psychologist*, *15*(2), 113.

Wilson, S. H., & Walker, G. (1993). Unemployment and health: a review. *Public health*, *107*(3), 153–162.

Yoo, K.-B., Park, E.-C., Jang, S.-Y., Kwon, J. A., Kim, S. J., Cho, K.-h., … Park, S. (2016). Association between employment status change and depression in korean adults. *BMJ open*, *6*(3), e008570.