Mental disorders and Mobile cell phone usage

An international comparison

by

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June 2019

Master's Programme in Economics

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Abstract

Mental health disorders and the cost associated with them for have long been a global burden. Recently a rise in mental disorders especially among the younger generations have been seen in a number of studies while the same group have seen a rapid change in mobile cell phone habits. This paper therefore aims to investigate potential connections between the mobile phone internet usage and mental disorders adding other social variables commonly used while measuring mental health. Three different regressions are made on international panel data to investigate change in mental health in the general population. Significant results cannot be found for mobile internet usage and many of the other variables are only significant in the last form of regression known for variance bias. For further and more significant research to be conducted the importance of a more common and systematically reported metric of the prevalence of mental disorders is stressed.

Key Words: Health Economics, Mental health, Mental Disorders, Mobile phone usage, SES

Acknowledgements

First and foremost, I must thank my supervisor Margareta Dackehag for well needed aid. Without Margareta's rapid and highly valid responses to my work this would have been much harder if not impossible and if you are a future student, I can highly recommend seeking her guidance.

Further acknowledgements go to all Lund's fun distractions and social life. Even though they have formed an unholy alliance to lower my grade they have given me both invaluable experience and the luxury of genuine interest in general learning, if not most about economics.

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Chapter 1 Introduction

Mental disorders are continually costing societies over the world, not only in human suffering but also vast amounts of economic output. An estimate from 2016 investigated aggregated investment opportunities for 36 countries, these countries bearing 80 % of the global disease burden for mental disorders. The results indicate that for every dollar invested in treatment of anxiety and depression the returns to investment would be in the region 3.3-5.7. (Chisholm *et al*. 2016).

In the EU, about 165 million are estimated to be affected as by 2016. Taken over a lifetime, over 50 % of the general population in middle- and high-income countries will at some point in their life have been subject to the condition mental illness. These illnesses affect a large part of the population, as by 2010 mental illness and substance use disorders was estimated to constitute 10,4 % of the global disease burden (Trautmann. *et al*. 2016).

What is easy to see in the last couple of years is that there has been an increase in mental disorders throughout the European Union. Peter Salmi (2017) writes for the Swedish social services, Socialstyrelsen, and reports as of 2017 the prevalence of mental disorders in Sweden has had an increase in excess of 100 % the last decade. In total this problem affects around 190 000 inhabitants considered young in Sweden and there is no apparent known cause for this rapid increase.

So, an important aspect when analyzing this increase is to look at areas where adolescents have seen a more rapid change than the general population. One area where adolescents have seen a change the last decade is within mobile phone usage. In Spain the age when individuals get introduced to cell phones gets increasingly younger. About 30 % of Spanish 10-year-olds own a cell phone with that number climbing fast with the individuals age within the dataset. The rate is 73 % for subjects 12 years of age and 83 % for 14 years of age. Furthermore, the introduction of handling smartphone devices can come as early as two to three years old as children habitually access their parents' phones (Gutiérrez *et al.* 2016).

This usage of mobile devices has many communication benefits but too much use and difficulties ignoring mobile devices can lead to addiction. A study from Deloitte estimate around 50 % of consumers check their phone within five minutes of getting up in the morning and 70 % of consumers check their phone at night. This dependence can cause sleep deprivation but also have other effects on mental health. In a study from India among medical student 40 % of the undergraduates expressed some degree of suffering from mobile phone addiction (Basu. *et al*. 2018).

Europe in general is ranked as the highest mobile phone usage region according to GSMA (2018) which is an organization representing interests of mobile operator worldwide. They use a metric called GMEI which takes all kinds of mobile internet phone usage like social media, e-commerce, entertainment and other phone services and produces as score for each country. More use among the ten case categories leads to a higher GMEI score and out of the four countries topping the list three is from Europe being Sweden, Finland, and Austria. Denmark also ranks high at seventh place in the ranking.

With previous research in mind this thesis aims to investigate if mobile phone internet usage along with more classical socioeconomic variables used in mental health studies have a relationship with mental disorders in a global panel data setting. The decision to compare countries and not microdata within a country comes mainly from access to datasets. Other research has primarily focused on socioeconomic variables and other environmental factors in a micro setting. This thesis though aims to investigate if mobile internet phone usage and socioeconomic factors influences mental disorders in a macro setting.

Optimally the variable prevalence of mental disorders would have been divided into age groups in order to only evaluate the group adolescents for whom mental disorders primarily have risen. To analyze the data obtained a fixed effect, random effects model and a mixed effect regression model has been used. The merged data covers 11 European countries over six years from three different databases. The countries are Belgium, Bulgaria, Denmark, Estonia, Finland, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia. The datasets used are the World Health Organization, Human development reports and Eurostat. The reason for choosing these countries is that only a handful of European countries have data obtainable for both prevalence of mental disorders and the other variables of interest mobile phone internet usage.
Furthermore, countries within the European Union share economic environment like the single market and customs union making them relatively homogenous research subjects. The

results obtained from this regression is positive but not significant for mobile phone usage on prevalence of mental disorders, all the other variables show significant results in accordance to previous research but with such a small sample definite conclusion cannot be made.

This study is structured as follows: In the next chapter a literature overview will be presented handling the subjects of mental disorders, mental health economics and mobile phone usage in order to provide tools for the analysis. Thereafter a chapter dealing with methodology and important aspects of the data. The fourth chapter will provide the results of the panel data regression followed by chapter five where analysis about this work will be made.

Chapter 2 Background and Theoretical Foundation

This chapter will provide a theoretical foundation for the subject at hand. A general definition of what mental disorders are and the problems surrounding the definition will be provided. This is followed by a brief overview of the psychological effects of mobile phone usage and finally how economist have handled the subject of mental disorder in previous research.

Definition of Mental disorder

Unfortunately, there has been very little uniformity of how to measure mental disorders. The measurement prevalence of mental disorder is relatively new and not yet commonly used in all research. Instead research often tries to approach the problem from either one of the diseases like depression or anxiety which make it hard to observe general mental health trends. Rickwood and Thomas (2012) stresses the importance for a standardized metric to be used across the mental health faculty suggesting prevalence of mental disorder. They say quote:
"It is evident that an agreed definition that supports the comparable measurement of help-seeking is lacking"
(Rickwood & Thomas, 2012, p. 173)

They continue to conclude that a more standardized measurement would significantly benefit comparisons across studies and population groups which in turn significantly will improve understanding of policies targeting mental health. A lot of the previous research therefore have some angle of analyzing mental disorders but often not in the sense of prevalence of mental disorders, rather one type of mental disorder like depression or proxies like anxiety. Therefore, the definition and further metric chosen is of importance to this paper in order to target mental disorders in general and not only the subcategories.

Mental disorders (or mental illness) can be defined as a behavioral or mental pattern that causes significant impairment of personal functioning. Bolton states 2009 that the standard manuals in psychiatric diagnosis are ICD-10 and DSM-IV which both have definitions of mental disorders. The crucial purpose of these definitions is to draw a distinction between when it becomes a disorder or illness instead of a social deviance. A key part of this

distinction is that a mental disorder is causing harm to the individual to some extent beyond control for the individual to deal with one one's own.
What is important in ICD-10 and DSM-IV is that mental disorder or illness is defined by individuals in distress or disability seeking help to get on with their lives (Bolton, 2009). Therefore, “mental disorders” is an umbrella term for multiple disorders which are more specific in how they affect the individual seeking help.

This is much in line with the world health organization’s definition of mental disorders. World Health Organization (2018) sate that mental disorders are characterized by abnormal thoughts, perceptions, emotions, behavior or and relationships with others. They further list that mental disorders include depression, bipolar affective disorder, schizophrenia and other psychoses, dementia, intellectual disabilities and developmental disorders including autism.

Linking mobile cell phone usage and mental disorders

Intuitively it may seem odd to associate mobile cell phone usage as a predictor for mental health but in the psychology field many studies have investigated how the stimulus from these devices effects the brain. Mobile phone usage has as told before risen dramatically mainly among the same age group (adolescents).

The link between mental disorders and lifestyle has sometimes been underestimated according to Walsh (2011). He argues there is a growing awareness about habits in lifestyle that can affect mental health and further therapeutic lifestyle changes can be as effective as psychotherapy or pharmacotherapy. It can therefore be worth exploring the populations lifestyles in order to investigate the rise in mental disorders such as mobile phone usage. As seen in the previous chapter mobile phone usage have been seen to cause mental disorders like depression or at least cause symptoms of mental disorders like anxiety, stress loneliness etc. that are symptoms of mental disorders according to World Health Organization (2018).

As more advanced functions on mobile phones is still relatively new so is the studies about the psychological effects from them. In 2009 a study conducted on 404 students in Barcelona, Spain found results indicating that psychological distress is related to both maladaptive use of both internet and mobile phones. Difference between genders were prevalent with females scoring higher in negative effects from maladaptive use of mobile phones (Beranuy. *et al.* 2009).

In 2012 Augner and Hacker (2012) investigated if problematic cell phone use correlated with different symptoms in the International Journal of Public Health. The analyzed answers from self-rated questionnaires given to 196 young adults found correlations between problematic cell phone usage and chronic stress, low emotional stability, female gender, young age, depression and extraversion.

This pattern seems to be present in later studies as well and that the emergence of social media on the mobile platform has played a role. The dependence and addiction to the mobile phones may at least partly come from mobile social media according to Hassan. *et al.* (2017) In his study a generation Y had a hard time letting go of mobile phones due to that many of their relations were handled through that medium. In this study handling and letting go of social interaction seem to be a key component in understanding the mobile addiction for those affected. Persons affected of mobile addiction in this study had as previous research negative impacts on health, self-esteem, depression, sleep disturbance, headaches, and loneliness.

The defining features of mobile phone addictions is according to the research above very similar and a lot of times directly causing mental disorders like for example depression in Hassan. *et al.* work (2017). It also seems to have effects on behaviors known to contribute to mental illness such as sleep deprivation, anxiety, stress, loneliness etc. Considering these similarities, studying this relationship might enhance the understanding of the nature of mental disorders.

Other links have been drawn between mobile phone use and mental health such as Višnjić *et al.* (2018) conducting research on 785 students in Serbia. They conclude that their results indicated that the intensity and modality of mobile phone use could be a factor that can influence causal pathways leading to mental health problems in the university student population. With signs linking mobile cell phone usage with mental disorders one can start analyzing how mental disorders have been discussed economically previously.

Economic research on mental health

According to Sen in 2012 there are mainly to competing but compatible theories about the causality of socioeconomic status and mental health. Longitudinal studies have shown that the individuals environment effect the individual’s mental health and from these findings comes the theory of social causation construct, this theory warrants investment in improving SES in

the long run to tackle mental disorders. On the other hand, cross sectional studies have shown support for the social selection theory arguing that improving mental health also improves SES in the short run. The consensus in the debate has been that both theories combined accounts for the majority of correlation between mental health and SES (Sen, 2012). This intriguing relationship should make analysis of panel data of interest as it could potentially capture all of the effects to give stronger estimates. Determining in what way causality goes is not a goal of this paper though, only to investigate potential relationships.
The literature finds clear patterns between mental disorders and productivity for individuals. Children with mental health problems suffers large negative consequences for both test scores and in the attainment level. In a study by Currie and Stabile (2007) about long term effect of mental health disorders among adolescents' significant negative results could be found between mental disorders and results in school. ADHD seemed to have the largest impact as one point in the hyperactivity scoring system almost completely correlated with retaking tests (0.8-1 percentage points) among US and Canadian children. The score in math for the same group dropped four to seven percent per score point in hyperactivity.

It seems from Currie and Stables work that there are more negative externalities from "externalizing" behavior disorders than "internalizing" ones. Depression for example affected the probability of retaking test similarly to ADHD but in contrast to the latter had no apparent effect on math scores or reading test scores.

The effect from mental illness on employment can be found for adults as employment rate is negatively correlated with mental health (Buffel, Straat & Bracke, 2015). It is important to stress though that these findings did not hold the same relationship for women between macro-economic factors and mental health and there is therefore a statistically significant gender difference.

Research about mental health economics examines the effect of unemployment on mental health and investigate if youth unemployment makes individuals more prone to mental illness during the remainder of their life. Significant results for poorer mental health at all target ages which were 21, 30 and 42 have been found for people who had experienced youth unemployment by Strandh *et al* (2014). The effect from the disease developed in childhood seem to have effects during the whole lifespan for the individual making mental disorders hard to recover from. More research regarding adolescent mental health and unemployment found a significant association between proportion of youth unemployed in the workforce and adolescents health problems in 10 European countries (Lager & Bremberg, 2009).

These findings seem to indicate a higher impact on mental health from unemployment when individuals are younger and a vaguer relationship in adulthood. What all the background research and literature have in common regarding unemployment and mental illness is the mentioning of the persistence of mental illness through ages. When an individual develops a sort of mental illness from unemployment in youth it seems generally to be hard to completely get back to better levels of mental health later in life.

The importance of income, education occupational status when analyzing mental illness or in this case mental distress has been argued since the 80-ties. Ronald C. Kessler examines the relationship in 1982 and finds that each of this SES-predictors is highly correlated with each other. For example, high income correlates highly with high education. Therefore, it can be hard to determine which of these factors that is most important for mental health. Finding from this papers data suggests income is the greatest determinant for men and education is the greatest determinant for women (Kessler, 1982). This stresses the importance of analyzing variables over time in mental health analysis.

Later work analyzes how social economic status effect on mental illness behave over time. McLeod and Shanahan (1993) investigate how poverty and especially the length of stay in poverty is important predictors for mental health. The results suggest the length of stay in poverty has a significant effect on mental health and that only measure poverty in itself can be misleading. Therefore, to only measure current income and SES may fail to capture the long-term effect on the mind from poverty.

Economic importance of mental health

The economic importance of preventing mental disorders can be seen through mental illness cost to society every year. When measuring cost to societies a matric called disability-adjusted life-years (DAYLs) is often used to calculate the magnitude of productivity loss from a given diseases as individuals cannot perform their regular jobs. The World Health Organization estimates that about 450 million people suffer from mental or behavioral disorders in the world costing developed countries an average of 3-4 % of GNP (World Health Organization, 2003).

Estimates by OECD finds that for any given year about one in six inhabitants in Europe is somehow affected by mental disorders negatively costing the EU in excess of 600 billion euro (more than 4% of GDP). A large part of those cost amounting around 260 billion comes from the higher unemployment and lower productivity coming with mental illness. The remaining part of the 600 billion was cost for social security (€170 billion) and healthcare expenditure (€190). In comparison the investment in defense represented 1,3 % of the European Union's GDP (Mathis, 2018).

The World Health Organization have recognized the problem and developed the Mental Health Action plan setting up goals between 2013-2030. Along with it came a thorough report handling mental health economics and how investment in the area could benefit developed and developing countries. The report, 'Investing in Mental Health evidence: Evidence for action' (2013) highlights as previous work first the current costs of mental illness. The following sentences sums the aggregated effects from the report up.
Quote:
'A recent analysis by the World Economic Forum estimated that the cumulative global impact of mental disorders in terms of lost economic output will amount to US$ 16 trillion over the next 20 years (3). Such an estimate marks mental health out as a highly significant concern not only for public health but also for economic development and societal welfare'
(World Health Organization, 2013, p. 7)

The reminding part of interest from this report by World Health Organization is the third chapter where evidence based (contrary to conceptual based in previous chapter) advantages of investments in mental health are presented. The return on investment is generally very good for all mental disorders, some measures like early intervention for psychosis, suicide prevention, and learning programmed for conduct disorder can have a return of 10 on the invested euro. Regarding the average improvement, recent research regarding investment of mental illness in South Asia and Sub-Saharan Africa. The return on every million-dollar invested was 500-1000 healthy years which is a very good payoff. These findings according to World Health Organization motivates spending and research to prevent mental illness on a broad scale.
With this productivity loss in mind it is important to investigate how, and which societal factors influence mental health in the population to limit unnecessary economic loss.

Economics and financial stability seem to be of importance for long term mental health or at least related to it. A broad study from Sweden conducted by Yunhwan and Hagquist (2018) evaluates adolescent mental health between 1988 and 2008 finds that the economic status and especially financial worry for the family seem to have effect on mental health. Especially during the 90-ties when Sweden had a major financial crisis with high unemployment rate this seemed to be the case unlike times of economic stability when a relationship between mental disorders and financial status was harder to find.

Chapter 3 Empirical Approach

This Chapter will give a description of the method used in this study to come up with the results. The section will go into model specification along with potential issues advantages and issues with the models used. Moreover, variables and assumptions made will be discussed in order to evaluate the data as there is no general established economic model for predicting mental illness as a result of socio-economic variables. Rather previous research has discussed different connections to mental illness and how these connections can influence the psyche. Therefore, this thesis will try to incorporate as many of the previous perspectives as possible along with internet mobile usage.

Empirical Specifications

The method chosen to analyze the relationship between mental illness and mobile phone usage in an international context is via fixed effects, random effects and lastly mixed effect estimations. This is conducted on several countries within the European union to see if patterns can be seen on international level.

First a Breusch-Pagan test will be made to assure usage of random effects in general over ordinary optimal least squares. The starting regression after the test will be a fixed effects model to investigate in what degree exogenous variables may be related to mental health controlling the intercept for country as done in previous research like Lindeboom, Portrait and van Den Berg (2002). With fixed effects estimators the specification looks as follows in equation *1*:

Equation (1)

$$y_{it} = X_{it}\beta + \alpha_i + \varepsilon_{it}$$

y_{it} = Prevalence of mental disorders for country i at time t

X_{it} = Observed exogenous variables for country i at time t

β = k*1 vector of parameters

α_i = Intercepts unique for each country

μ_{it} = The error term for country i at time t

The exogenous variables used from previous research is indicators for education, disposable income, Gini coefficient, poverty, internet accessed through mobile phones and unemployment.

After the fixed effects regression has been run and evaluated the random effects model for the countries will be tested. An advantage with a more random effects approach is that the analysis is interested in what effects mental disorders and not the difference between countries per se. To explore exogenous effects on mental disorders we assign randomness to the slopes depending on country and time which might explain a lot of the variance in the dataset.

A problem with choosing between fixed effects and random effects is that random effects have an assumption when used that the individual specific effects are uncorrelated with the independent variable. This is clearly not the case looking short term as countries unemployment, education etc. change slowly and may therefore in short term be considered fixed to an individual country. Consider a longer time span on the other hand, country or geographic region within the European Union might not be a determinant for our exogenous variables. The time span as noted is only six years, therefore both models will be run with this in mind. To help us determine what approach is more suitable a Hausman test will be run to see if random effects can be excluded in favor of fixed effects.

When the random effects regression has been run a mixture of the two will be tested. This is equivalent of generating six time period random effects plus 11 country specific intercepts and slopes resulting in 17 different random effects. In a crossed effect model, it could be argued to be 17 different groups, but one could also model as if the data is treated as one group with 17 random coefficients on the whole dataset, all individuals gets their own regression. As intercepts can vary for time and individual such as in fixed effects model but also slopes may vary as in random effects model this is usually called a mixed effects model.

Furthermore, McNeish and Kelley, (2019) states that mixed estimations on small clusters face the risk of bias the variance downward which must be taken into consideration during analysis. Considering the above it is hard to exclude any of the regressions in favor of another. Random and fixed effects both have advantages due to better stability in variance and neither can be excluded by the Breusch-Pagan test. Mixed effect on the other hand brings more dynamics to each individual countries' relationship between variables and Mental disorders. In order to get a more complete picture of the relationship this paper includes all three types of regression.

A pure random effect model would look as follows in equation 2:

Equation (2)

$$y_{it} = \mu + W_{it}$$

y_{it} = Same as fixed effects model

μ = Mean for entire population

W_{it} = Country specific random effect at time t

The specification for the mixed model looks as equation 3 with further explanations on the next page:

Equation (3)

$$\overbrace{\boldsymbol{y}}^{\text{N x 1}} = \overbrace{\underbrace{\boldsymbol{X}}_{\text{N x p}} \underbrace{\boldsymbol{\beta}}_{\text{p x 1}}}^{\text{N x 1}} + \overbrace{\underbrace{\boldsymbol{Z}}_{\text{N x q}} \underbrace{\boldsymbol{u}}_{\text{q x 1}}}^{\text{N x 1}} + \overbrace{\varepsilon}^{\text{N x 1}}$$

Notation	Dimension	Unit
Y	N*1	*Column vector of Prevalence of Mental Disorders*
X	N*p	*Predictor variable matrix*
β	p*1	*Vector of estimates*
Z	N*q	*Design matrix for random effects*
u	q*1	*Unknown vector of random effects with mean 0*
ε	N*1	*vector of error terms*

Notation	Contents
q	*[Belgium, Bulgaria, Denmark, Estonia, Finland, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia]*
N	*44 matched observations*
p	*[1 Mobile_use Unemployment Gini_coefficient Education Disposible_income Poverty_or_social_exclusion]*

General problems with multicollinearity should be analyzed as many of the variables are expected to be correlated such as education and income. (Sirnio, Martikainen & Kauppinen, 2013) This is done by analyzing the correlation matrix of the mixed model.

Endogeneity concerns are valid as well as mental disorders has in previous research effects on schooling like drop-out rate which affects education index. It is also likely according to previous research that mental disorders have impacts on unemployment, disposable income and poverty or social exclusion. This is done by a Wooldridge test for autocorrelation in the panel data.

Finally, normality will be analyzed with a Sharpio-Wilk test for normality and a plot of the error distribution in order to see if the error terms show consistency.

Data Review

The data used for this paper is panel data and originates from three sources, the World Health Organization Regional office for Europe database, the Human Development database from Human Development Reports and the Eurostat database. The matched data for all variables contains 44 perfectly matching observations in total with 11 countries over the six years 2011-2016. This means that in 44 cases the data point match for all variables in contrast to when a data point may be lacking. This is the reason why the number of matched observations in the regression (44) is less than each variable individual observation (at least 48). An example is Bulgaria in 2014 have data on all variables except poverty and social exclusion. Therefore, even though this is not counted towards the 44 matching observations in the regression they are counted as one variable observation for all but poverty and social exclusion in table (1) – Variable overview.

The 11 countries are Belgium, Bulgaria, Denmark, Estonia, Finland, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia which all are members of the European Union. The reason for choosing these particular countries is mainly for the access to good data on both mental health and societal statistics, furthermore the relative similarity of development and economic structure within the region make the countries more comparable than other regions. Central Asia for example has reported documentation on mental illness but have expected higher deviation in economic systems between each other than countries within the trade union and single market of the European Union.

Table (1) - Variable overview

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	66	2013.5	1.720912	2011	2016
Prevelence~r	48	3.558125	2.286202	1.12	7.5
Countryname	0				
Mobile_use	66	34.06061	19.26007	3	78
Unemployment	66	9.378788	2.619602	5.1	16.2
GINI_coeff~t	63	30.45079	4.228813	23.7	37.9
Disposible~e	65	15848.75	5064.599	8678	25061
countrynum~r	66	7.545455	3.629714	2	13
Povert_or_~n	62	27.47419	9.104492	16	49.3
Education_~x	66	.8489091	.0467599	.76	.941

Variable	Measurement	Source
Prevalence of mental disorder	*Prevalence of mental disorders*	*World Health Organization*
Mobile use	*Percentage of individuals used a mobile phone (or smart phone) to access the internet*	*Eurostat*
Unemployment	*Unemployment by age and sec – annual average*	*Eurostat*
Gini coefficient	*Gini coefficient of equalized disposable income*	*Eurostat*
Education	*Education index*	*Human Development Reports*

Disposable income	*Adjusted gross disposable income of household per capita in PPS*	*Eurostat*
Poverty and social exclusion	*Share of population at risk for poverty or social exclusion*	*Eurostat*

The data used was collected from international institutions with very high reliability, the problem lies in the reporting from countries in these datasets.

Some countries in the European dataset have remarks regarding the numbers given such as break in time series, estimated number, low reliability, not significant etc. All numbers are used though as they seem reasonable and have been considered good enough for the European Union to report and they are based on yearly surveys.

In the WHO database different descriptions are given for every country on how the estimates was produced. What is important for this work is that all reports are reported by the World Health Organization as prevalence of mental disorders. No remarks have been given by the WHO about the quality or lack of quality of the indicators such as Eurostat.

The World Development Reports database offer no comments on the data provided apart from source.

Reviewing the variables, the dependent variable represented by y will be prevalence of mental disorders collected from the World Health Organization. World Health Organization – Regional office for Europe (2018) notes that prevalence of mental disorder share definition with parent indicator “All cases of mental disorders at years end” and that the measurement reported is: The cumulative number of registered mental patients at end of calendar year (chapter 5 of ICD 9/10). The parent indicator as can be seen directly refers to the literature in chapter 2 regarding the definition of mental disorders. This further means that the variable of choice prevalence of mental disorder is “All cases if mental disorders at years end” divided by the total population at years end to obtain prevalence of mental disorders. This measurement makes prevalence of mental disorders a register data type.

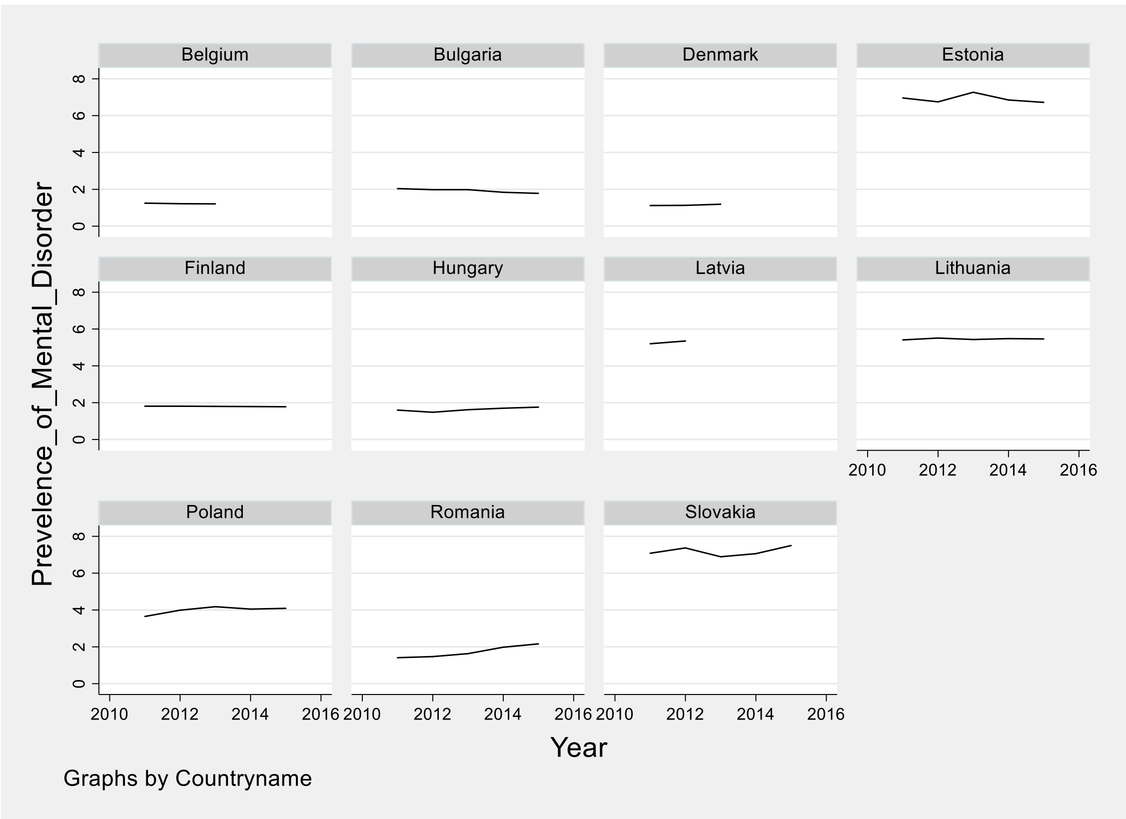
The data in the HFA database where prevalence of mental disorders resides comes from various sources according to World Health Organization – Regional office for Europe (2018). Those sources are country experts, WHO/Europe’s technical programmes, and partner organizations as Eurostat, the Organization for Economic Co-operation and Development, and

United Nations agencies. The database has reported essential health related statistics since the mid-80s, and the data is updated annually.

There are a couple of aspects to consider regarding this variable, first and foremost choosing prevalence of mental disorders to measure social economic effects in a given period can be problematic as this this is likely affected from socioeconomic variables with a lag. Luckily our model and the fact that there are six time periods should deal with this problem decently, an optimal dependent variable for the regression analysis would be more sensitive to instant change in the exogenous variables.

Secondly prevalence of mental disorders data from WHO is sporadic at best, many countries in and around Europe lack good estimates or have so few measurement points in time that they become unworkable in a panel data setting. More observations over both cross section and time would make analysis more precise and significant. As can be seen in Table (1) - Variable overview and Plot (1) Latvia especially lacks consistency in the reporting prevalence of mental disorder.

Plot (1)



Other proxies have been considered for measuring mental illness on an international level but the other data available is almost always estimations of cost of care, people institutionalized for mental health or morbidity statistics. The problem with the first proxy is that countries does not necessarily adjust spending on mental health because of a rise in the same. The other two proxies share the problem of completely failing to capture increases in mental illness not resulting in institutionalization or death. As mentioned in the previous chapter many people live normal but impaired lives with mental illness making these proxies poor estimates.

The first of the exogenous variables of interest is mobile phone usage and especially internet use on the device. This metric is taken from Eurostat and is in its full indicator definition: “Individuals used a mobile phone (or smart phone) to access the internet”. The reason why the timeline for the merged dataset starts at 2011 is this variables timespan, Eurostat both added new variables like this one and made changes in how variables are measured in 2011.

A problem with mobile phone usage is its inability to measure social media usage pinpointed in some of the previous research. The main topic of the previous research is internet mobile phone usage in general and therefore this should be a good estimator. Additional parameters for type of mobile internet usage would have been interesting but the only data found regarding purpose of mobile internet use is cross sectional for year 2012 from Eurostat.

Unemployment, Gini coefficient and disposable income data was all obtained from Eurostat with indicator definitions “Unemployment level by sex and age - annual average”, “Gini coefficient of equivalized disposable income” and “Adjusted gross disposable income of households per capita in PPS”. PPS is an artificial purchasing power adjusted unit that in theory can buy the same amount of services and goods in each country thereby accounting for difference in currency. Eurostat provides good estimates for precisely what previous research addresses in these areas and the data is almost perfectly consistent across the timespan for all countries.

The last of the exogenous variable taken from Eurostat is risk of poverty and social exclusion. As mentioned in previous research poverty and length of stay in poverty seem to adversely affect mental health. A good poverty indicator from Eurostat is risk of poverty or social exclusion as that estimate a sort of relative poverty for a given country.

The explanation and calculation of this metric is rather complex and therefore worth analyzing. According to Eurostat (2019) risk of poverty or social exclusion corresponds to the share of the population who are either at risk of poverty, severely materially deprived or living in a household with very low working intensity. Individuals are counted once regardless of how many of these criteria they fulfill. At risk of poverty is defined as persons living below the risk-of-poverty threshold set to 60 % of national median equalized disposable income. Severe material deprivation is determined by if the individual fulfill four out of nine materialistic sub criteria or not. Finally, people living in households with very low work intensity are people aged 0-59 living in households where adults (aged 18-59) work 20 % or less last year of their work potential.

Given all criteria's above this variable seem to be easy for countries to have high estimates in but also rather hard to lower as countries developed due to mainly two reasons. The first is the number of criteria for this indicator is making it hard from developed countries to lower their statistics. For instance, a country fulfilling only one poverty or social exclusion criteria for an individual will be rated as good as a country where another individual fulfills all. The second reason is that the coefficient is related by the 60 % rule to disposable income and Gini coefficient punishing richer countries with high Gini. This point also makes this variable multicollinear with disposable income and Gini coefficient which need to be addressed in the analysis.

The final variable is education and the indicator used for measuring countries level of education is the education index by Human Development Reports. This indicator is calculated as average of mean years of schooling index and expected years of schooling index. This produces a standardized number for every country in the span [0 1]. This is an accurate way to compare education between countries even though one could argue it only measures quantity, not quality of time provided in school. In plot 1 the average stands at approximately 0.85, this can be compared to Poland measuring 0.852 having 16.4 expected years of schooling and 11.9 mean years of schooling (Human Development Reports, 2019). The organization further states that they use multiple sources for their data containing both register and survey methods for estimates.

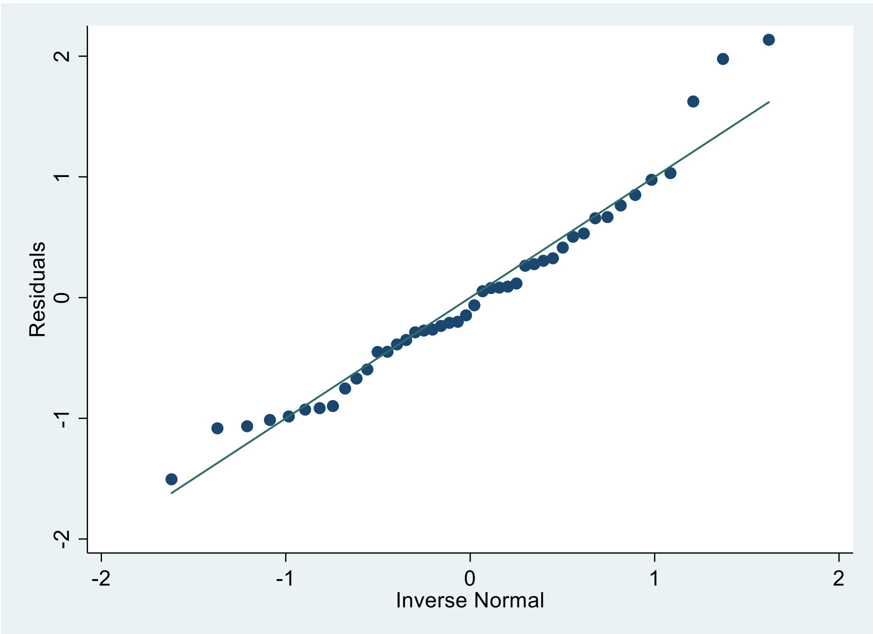
To sum up the overview of the variables the limitation of the data is that it lacks coherence and grouping of interest like gender and especially age. The regression analysis would preferably have been done on a thorough micro panel-set to investigate proxies and groups especially highlighted in previous research rather than a patchy macro panel-set. The assumption that change in subgroups mental health like adolescents and females should affect the statistics for the whole population is key for the regression. In other word a rise in mental disorders among for example females under 25 should produce a rise in that country's total prevalence of mental disorders all else equal.

Chapter 4 Empirical Results

In this chapter results from the data analysis will be presented. The results will be discussed and put into the subject's context. Three different regressions are run, first a fixed effects estimate followed by a pure random effect and finally a mixed effects maximum likelihood estimate without grouping where slopes can vary freely. Test are analyzed but found in the appendix while descriptive plots and regressions are presented within the chapter.

As can be seen by the Breusch-Pagan test random effects should indeed be incorporated in favor of using standard OLS, see test 1 in appendix. Evaluations for autocorrelation and endogeneity in test 3 in the appendix tells us that according to Wooldridge test with a F-probability of 38 % there seem to be no significant sign of first order correlation. Note that $H_0$is there is no autocorrelation which we cannot reject in favor H_1 of some autocorrelation. Analyzing normality there mainly seems to be a problem with variables Mobile use and Education according to test 4 in the appendix which is a concern as especially education have a relatively large impact on mental disorders according to regressions. Both variables have probabilities of slightly more than 6 % in test 4 making them close to significantly normal but not quite. As can be seen in plot (2) especially the extreme errors accounts for two of the variables failing normality.

Plot (2)



A unit root test can be seen in test 5 indicating that unit root is not a large issue for this data. All test types come out with a probability of zero flat rounding to four decimals. Finally, multicollinearity is analyzed through the correlation matrix named test 6 in the appendix between the estimates. Note that if variables are positively correlated then the estimates of the same tend to be negatively correlated in the correlation plot for estimates. Looking at test 6 there are plenty of variables having high correlations as expected, especially education and disposable income have a high correlation which is strongly supported by previous research. Other societal variables have correlations in excess of 0.5 which was to be expected. All variables are kept as they have been important predictors in previous research.

The Hausman test between random and fixed effects suggest we cannot reject the null hypothesis though with a fine margin as can be seen in test 2 in the appendix. The null hypothesis in this case is that variables are random given country, this cannot be rejected. Worth noting is the purpose of this test is to evaluate the use of random effects but not specifically evaluate the use of mixed effects regression. This may indicate the possibility to use of random slopes by pure random effects and mixed effect regressions to some extent.

In regression (1) with fixed effects on the next page none of the X-variables have a significant effect on prevalence of mental disorders. The variable mobile use has a P value of 65.8 %, making it more likely that beta for this variable does not have effect on mental disorders. These results come mainly from the variance within groups them self, making up for 99.5 % of the total variance as can be seen by rho. This first regression where all countries have different intercepts but the same effects on Mental health cannot say much at all as the F-test states it is more likely all variables are zero than distinctly different from it. Worth noting in this model is that Gini coefficient and disposable income have the opposite relationship with mental disorders than predictions from previous research. In general, the relationships between variables of interest and mental disorders in this regression with fixed effects are weak and random.

VARIABLES	(1) Fixed effect regression
Mobile use	-0.00275
	(0.00615)
Unemployment	0.0252
	(0.0339)
GINI coefficient	-0.00730
	(0.0351)
Disposable income	0.000128
	(0.000105)
Poverty or social exclusion	-0.0260
	(0.0228)
Education index	-4.898
	(3.193)
Constant	6.588**
	(3.015)
Observations	44
Number of Countries	11
R-squared	0.158

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Continuing with the pure random effects model in regression (2) one can start to see patterns suggested by previous research. Mobile use, unemployment and Gini coefficient affecting mental disorder positively while the others seem to affect mental disorders negatively. None of the parameters are significant and approximately 95 % of the variance is still within the countries seen by the rho estimate.

It seems like mental health is by far most influenced by the education index if these insignificant results are to be believed.
Note that Poverty and social exclusion seem to have a negative relationship with mental disorders which seems counterintuitive. This might be to poverties' positive correlation with disposable income as mentioned in the previous chapter.

VARIABLES	(2) Random effect regression
Mobile use	0.00902
	(0.00745)
Unemployment	0.0586
	(0.0515)
GINI coefficient	0.0394
	(0.0515)
Disposable income	-0.000131
	(9.93e-05)
Poverty or social exclusion	-0.0636*
	(0.0331)
Education index	-3.709
	(4.985)
Constant	8.397*
	(4.602)
Observations	44
Number of Countries	11

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In mixed regression (3), the mixed regression model on the next page where there is only one group with individual specific intercepts and slopes, we get more significant results. The variable Mobile use is also here positive but not significant and therefore a relationship cannot be established. The effect is very small at 0.009 percentage points increase in mental disorders for every percentage point increase in the mobile phone use metric, only disposable income seems to have a smaller effect. What can be seen in this regression model as in the previous one with pure random effects is results more in line with previous research regarding most socioeconomic variables. Note that the importance of the education index has more than tripled in this regression compared to the previous two. Gini coefficient with beta 0.36 and unemployment with beta 0.48 seem to be more important than disposable income for the mental health status of countries. The random effects parameters measure how much of the variance that is affected by random effects parameters which as expected from previous regressions is high at 63.4 %. As noted in Chapter 3 these sorts of mixed regressions have been seen to bias variance downwards with small clusters and therefore one should be careful reading too much into these results.

	(3)	
VARIABLES	Mixed regression	Residual
Mobile use	0.00907	
	(0.0112)	
Unemployment	0.479***	
	(0.0547)	
GINI coefficient	0.361***	
	(0.0543)	
Disposable income	-0.000305***	
	(6.68e-05)	
Poverty or social exclusion	-0.357***	
	(0.0295)	
Education index	-11.87**	
	(6.012)	
Constant	12.31***	-0.227**
	(4.245)	(0.107)
Observations	44	44

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Chapter 5 Discussion

Mental disorders continue to cost society vast amounts of resources but in order to construct effective policy, common metrics must be installed for large scale research on the subject. Without samples large enough for qualitative analysis easily accessible, research on mental health as a general phenomenon will suffer. A broader term like prevalence of mental disorders need to be reported more frequently on a global scale in order to analyze most of the mental disorder, including those cases leading to impairment but not institutionalization or suicide.

The aim of this study was to investigate if mobile phone internet usage along with more classical socioeconomic variables used in mental health studies have a relationship with mental disorders in a global panel data setting. Using panel data regression with fixed, random and mixed effects significant results where hard to obtain and even the ones obtained should be viewed with caution. Mixed effects on all estimates on small clusters are known to cause downward bias in the variance (McNeish & Kelley, 2019).

Further assumptions regarding independence between the ID variable country and other exogenous variables is a very strong assumption even inside the EU which is an assumption used with random effects estimate. The result of the Hausman cannot with significance exclude the use of random effect even though with a fine margin and therefore random effects or mixed effects might be of use. Further the normality test raises concern over the strongest predictors (education index) and mobile use effect on mental health. As the deviations comes from extreme vales and is only just insignificant the variables are still included but normality is all the same violated.

The variable of interest for this paper was internet usage by mobile and smart phone and if adverse mental health effects from previous research on adolescents could be spotted on a national level. This relationship was impossible to establish with data available but further research on more targeted population with more observations seem encouraged from previous research. Other more commonly used SES variables seems to have a larger impact even though they too are hard to distinguish from such a limited dataset.

Mobile usage and mobile phone addiction are still to a large extent unexplored on a societal level with most previous psychological research conducted on small cohorts of students or the young like the works of McNeish and Kelley (2019) or Beranuy. *et al.* (2009). Other studies like Gutiérrez *et al.* (2016) focus more on overuse and frequency on mobile use but also in a micro setting. As these sorts of studies seem to find mental effects of internet access through mobile phones more societal research could be interesting even though it seems like other environmental factors would be of higher priority.

The link between socioeconomic variables and mental health is indicated throughout previous research and it continuous to show through this paper even though with as mentioned weak scientific reliability. Education especially seems to be important even though the large deviation between countries make it hard to estimate to what extent. The question for further research regarding SES variables not handled in this paper is to investigate the long run causality of mental health. Again, this causality needs a much more rigorous and coherent reporting metric globally to be analyzed properly on a larger scale than previous research.

Research like Strandh. *et al.* (2014) seem to indicate that mental disorders are not only costly but also hard to eradicate later in an individual's life. Environmental variables affecting adolescents need to be better researched in order to understand which of those variables that are associated with the current rise of mental disorders within that group. Succeeding and quickly implementing targeted policy will most likely to some extent prevent or hamper a future rise in the global disease burden for mental disorders. As estimates suggest an average cost of three to four percent of GNP yearly from mental disorders in developed countries (World Health Organization, 2003) and treatment seem cost effective the payoff could be substantial, both in monetary and humanitarian terms.

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Appendix

Test 1.

```
Breusch and Pagan Lagrangian multiplier test for random effects

        Prevelence_of_Mental_Disorder[countrynumber,t] = Xb + u[countrynumber] + e[countrynumber,t]

        Estimated results:
                         |       Var     sd = sqrt(Var)
                ---------+-----------------------------
                Prevele~r |   5.148012       2.268923
                        e |   .0328293       .1811886
                        u |   .6232166       .7894407

        Test:   Var(u) = 0
                             chibar2(01) =     4.45
                          Prob > chibar2 =   0.0174
```

Test 2.

```
                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |      fe           re          Difference          S.E.
-------------+----------------------------------------------------------------
  Mobile_use |   -.0027518     .0090216       -.0117734               .
Unemployment |    .0252205     .0585908       -.0333703               .
GINI_coeff~t |   -.0073013     .0393777        -.046679               .
Disposible~e |    .0001283    -.0001307         .000259        .0000337
Povert_or_~n |   -.0260177     -.063574        .0375563               .
Education_~x |   -4.898164    -3.709252       -1.188912               .
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                  chi2(5) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       10.50
                Prob>chi2 =      0.0623
                (V_b-V_B is not positive definite)
```

Test 3.

```
Wooldridge test for autocorrelation in panel data
H0: no first-order autocorrelation
    F(  1,       8) =      0.871
           Prob > F =      0.3780
```

Test 4.

```
                   Shapiro-Wilk W test for normal data

    Variable |        Obs       W           V         z       Prob>z
-------------+------------------------------------------------------
Prevelence~r |         48    0.82505      7.968     4.415    0.00001
  Mobile_use |         66    0.96581      2.006     1.509    0.06562
Unemployment |         66    0.94358      3.311     2.595    0.00473
GINI_coeff~t |         63    0.91143      5.007     3.482    0.00025
Disposible~e |         65    0.88425      6.710     4.122    0.00002
Povert_or_~n |         62    0.91940      4.498     3.247    0.00058
Education_~x |         66    0.96536      2.033     1.537    0.06209
```

Test 5.

Fisher-type unit-root test for Prevelence_of_Mental_Disorder
Based on augmented Dickey-Fuller tests

```
Ho: All panels contain unit roots           Number of panels       =     11
Ha: At least one panel is stationary        Avg. number of periods =   4.36

AR parameter: Panel-specific                Asymptotics: T -> Infinity
Panel means:  Included
Time trend:   Included
Drift term:   Not included                  ADF regressions: 0 lags
```

		Statistic	p-value
Inverse chi-squared(20)	P	133.6724	0.0000
Inverse normal	Z	-3.9662	0.0000
Inverse logit t(39)	L*	-12.1378	0.0000
Modified inv. chi-squared	Pm	17.9732	0.0000

P statistic requires number of panels to be finite.
Other statistics are suitable for finite or infinite number of panels.

.

Test 6.

Correlation matrix of coefficients of xtmixed model

e(V)	Prevel~r Mobile~e	Unempl~t	GINI_c~t	Dispos~e	Povert~n	Educat~x	_cons	lnsig_e _cons
Prevelence~r								
Mobile_use	1.0000							
Unemployment	0.2430	1.0000						
GINI_coeff~t	-0.0833	0.3267	1.0000					
Disposible~e	-0.2297	0.4108	0.5483	1.0000				
Povert_or_~n	0.2543	-0.0529	-0.5825	-0.0292	1.0000			
Education_~x	0.0067	-0.3221	-0.5677	-0.6530	0.5081	1.0000		
_cons	-0.0757	0.0229	0.2369	0.2977	-0.5813	-0.8760	1.0000	
lnsig_e								
_cons	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000