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Understanding the impact of demographic and environmental factors on mental health during COVID-19

An empirical study of Norwegian mental health data from November and December 2020.

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Preface

This thesis marks the end of our Master's degree at Oslo Metropolitan University.
It has been a rather unique semester, and COVID-19 has certainly played its part.

We want to start off by expressing our gratitude towards our supervisor Tapas Kundu at OsloMet for extensive discussions, well thought out suggestions, support and guidance throughout the writing of the thesis. We would also like to thank Thomas Sevenius Nilsen at FHI for providing the dataset which made our research feasible.

We also want to thank our family and friends for sticking with us during a challenging, but rewarding process. In the end, we would also like to give a shout-out to our Fantasy Football group, which consists of great colleagues and friends.

Abstract

The research question looks at the role that gender, age, education, economic situation, unemployment, and singlehood play on the probability of having considerable mental health problems during the COVID-19 pandemic. We have used a multiple logistic regression model on a dataset from November and December 2020 from FHI, to answer the research question. The dataset limits us to a population of Oslo, Agder, Nordland and Vestland.

To summarize the research question; gender, age, economic situation, unemployment, and singlehood all play a role on the probability of having considerable mental health problems during the COVID-19 pandemic. Being a woman, being in the younger age groups, having economic challenges, unemployment and being single are all associated with a higher probability of having considerable mental health problems during the pandemic.

Knowing what role the explanatory factors play on the probability of having considerable mental health problems may also be valuable for policy decisions if we were to find ourselves in a similar situation in the future. By seeing the prevalence of mental health problems in the different groups during the pandemic, policy makers should try to ensure that these exposed groups receive proper consideration before decisions are made.

We hope that this thesis can inspire future research on what we believe to be an immensely important subject. The economic cost of these problems is extensive, and more importantly - the human cost is unaffordable.

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1 Introduction

1.1 Introduction and research question

Mental health problems have been a widespread form of illness since the beginning of time. To this day, mental health is still a subject that is considered to be taboo in some places around the world. Efforts such as mental health awareness campaigns have contributed to raising conversation concerning depression, anxiety, eating disorders and other mental illnesses in order to normalize seeking help. The World Health Organization (WHO)[1] expects mental health to become the leading cause of disease burden globally by 2030, and the respective cost to be US$ 6 trillion a year. This is equivalent to a 140% increase from the US$ 2.5 trillion at the time of the publication of the report (WHO, 2011).

In Norway, mental health problems account for 19.6% of the total health care treatment expenditures, which equates to NOK 37.2 billion. The expenditure for treating mental health problems is higher than any other form of disease in Norway. At any given point of time, around 7% of the Norwegian workforce are on sick leave (OECD, 2013). In 2015, around 20% of those on sick leave stated mental health problems as the cause (Helsedirektoratet, 2019). The Norwegian welfare system is lenient when it comes to sick leave, with its population being compensated for up to a year of absence from work.
WHO's prognosis about the coming global increase in mental health problems should raise concern for Norwegian policy makers, due to the already high sick leave percentage and the massive expenditures related to this (WHO, 2011).

In March of 2020, the pandemic caused a comprehensive lockdown which affected every individual in Norway to some extent. Not only did it cause a massive decline in demand for goods which forced the economy into a recession, but it also caused hundreds of thousands of people to be on furlough in order to reduce the risk of spreading the disease. Research has highlighted poor personal economy and unemployment as some of the explanatory factors for increased risk of

[1] Hereby referred to as WHO

having mental health problems (FHI, 2011). Both of these factors have been affected by the pandemic (NAV, 2020).

Due to the unique circumstances of the lockdown and pandemic, we were interested in researching how some explanatory variables affect the probability of having mental health problems during this period. Our research question is therefore:

"What roles do gender, age, education, economic situation, unemployment, and singlehood play on the probability of having considerable mental health problems during the COVID-19 pandemic?"

Earlier research indicate that the prevalence of mental health problems may be higher during recessions (Bambra et al. 2010). A possible explanation for this is the increased unemployment rate which causes reduced income and societal exclusion, as well as higher stress levels compared to before the recession (Drydakis, 2015). The situation we are in right now, however, is different from a typical recession. Whereas a typical recession is caused by a bubble in the financial sector, this recession has been caused by a sudden shutdown of the economy, leading to a massive, negative shift in the demand of goods and services. The dynamics are therefore different compared to earlier recessions (Holden & Wulfsberg, 2020).

We will attempt to answer the research question by using a logistic probability model. We got in touch with representatives from Folkehelseinstituttet (FHI)[2] and were able to get access to a classified dataset, which laid the foundation for the thesis. The dataset included five questions from the Hopkins Symptoms Checklist (HSCL-5)[3] which measures considerable mental health problems. The dataset only contains data from the months of November and December 2020, and from certain parts of Norway. This limits the scope of our thesis.

We compared our findings with earlier research and found that most of our results were consistent with their results. E.g., we found a higher probability of having mental health problems in the younger age groups compared to the older. This is in accordance with earlier research done by FHI which showed the same result (FHI, 2011). However, a higher percentage of our younger

[2] Hereby referred to as FHI
[3] Hereby referred to as HSCL-5

age group had considerable mental health problems compared to the 2011 FHI report. The pandemic may be an aggregator for this difference.

1.2 Thesis structure:

Chapter 2 of the thesis is the literature review, which is divided into three sections. In the first section we look at some of the explanatory factors for mental health problems based on empirical research. In the second part we go in depth into some earlier Norwegian research on mental health problems. We also review research from other countries for mental health problems during recessions. Additionally, we will go through a research paper from the U.S that was conducted during the pandemic. In the last section, we summarize the findings from the presented research that are relevant to our research question.

Chapter 3 is the background chapter. We begin the chapter by looking at the costs of mental health problems. Afterwards we look at how the Norwegian system functions in regard to those who are struggling with mental health problems. Lastly, we look at how the pandemic has affected our lives and look at which groups have been the most affected in Norway.

In chapter 4 we present the empirical strategy we use in order to answer our research question. Choice of estimation model, limitations and challenges with the model are discussed in this chapter. In chapter 5 we discuss the dataset we have acquired and each variable in the model is described in detail. We present and interpret our findings in chapter 6, before we discuss and conclude our thesis in chapter 7.

2 Literature review

2.1 Explanatory factors

Mental health problems are caused by many different explanatory factors. The factors exist in the form of social, environmental, cultural- and genetic factors, among others. It is thought that each factor in themselves has a small effect (Fryers & Brugha, 2013). One specific factor is not enough for mental health problems to exist; however, different combinations of explanatory factors can lead to mental health problems (Susser, 2006).

All explanatory factors are not necessarily risk factors but can also be protective factors. Some may also be a combination of both. An example of this is a romantic relationship. A stable romantic relationship can protect against mental health problems as a form of social support, which is defined as having emotional contact, as well as having a network around you (Fyrand, 1994). However, if the relationship ends, it can be a burdensome life event that increases the risk of developing mental health problems (Amato & James, 2010).

It can be hard to pinpoint cause and effect for explanatory factors for mental health problems, especially when it comes to social factors. Education is an example of this. Lower education can create difficulties entering the labor market, and this can be a cause of stress. Stress can be a contributing factor for having a higher risk of mental health problems. On the other hand, having a mental health problem can also be the cause of having lower education, due to education being too demanding (FHI, 2006).
In the next section we will try to shed light on some of the most relevant factors for our thesis.

2.2 Environmental and demographic factors

Environmental factors can be both risk factors and protective factors. They include both interpersonal and economic factors, as well as the social structure (Bronfenbrenner, 1986). It is, in simple terms, the effect of the people and society around us. Education, economy, social support and conflicts and life events are some examples of environmental factors.

While environmental factors revolve around the society around us, demographic factors provide more general information about the individual. Some examples of demographic factors are race, age, gender, and ethnicity. We will now go into more detail on some environmental and demographic factors.

Social support and social participation

Research has shown that both participating socially and having social support have a positive effect on mental health (Fyrand, 1994; Dalgard et al., 2006). On the other hand, lack of social support and social participation is associated with increased risk for mental health problems (FHI, 2011). This was further supported by Dalgard et al, who found that those lacking social support, and who experienced burdensome life events later on, had a higher probability of having mental health problems (Dalgard et al, 1995 & Dalgard et al, 2006). They further discussed that having good social support would act as a buffer against these burdensome life events making the individuals better equipped to deal with them.

In FHI's report from 2011 on mental health in Norway, they found that Norwegians scored higher when it came to social contact, trust, affiliation, and support from local environment, compared to other countries in Europe. Social support was found to have a downward trend with age, with the older age groups experiencing less social support (FHI 2011).

Education and economy

The relationship between education and mental health problems has been widely studied and proven to be correlated. In Norway there has been found a significant association between level of education and mental problems for both genders (Dalgard et al., 2007). There are, however, some mediating factors which might affect the estimation of the effects that education has on mental health. Having an education may give a sense of mastery and accomplishment which may contribute to good mental health (Dalgard et al., 2007). Education may also contribute to increased stress levels due to difficulties in the job market and the scarcity of jobs that do not require education. It is difficult to be certain about the causal effect, as the relation can go both ways. If you suffer from mental problems, finishing an education may be more challenging. Thus, one may refrain from getting an education (FHI, 2006).

Being under the poverty line is associated with increased risk for mental health problems. This might be explained by increased stress levels. Additionally, the study also found an increased risk of being bullied among the youth (Due, Damsgaard, Lund, & Holstein, 2009). However, the FHI research from 2011 found that living under the poverty line is less impactful than suddenly experiencing serious economic problems (FHI, 2011). On the other hand, having a good and stable economy is widely reported as positively correlated with good mental health (Helsedirektoratet, 2014).

Education and personal economy may also affect each other. In general, individuals with a higher education are more likely to have a stable economy. For that reason, some of the effect education has on mental problems may also be captured in personal economy (FHI, 2011).

Unemployment

There is a strong correlation between unemployment and mental health problems, which may appear in different circumstances. There is a negative mental health effect when initially losing a job as well as when you have been unemployed for a while (Modini et al., 2016). The workplace is important for sustaining good mental health as it gives the individual a purpose, as well as the feeling of mastery and having a sustainable and safe economy. In the FHI report from 2011, they found that having been unemployed for the past three months increases the risk of having significant mental health problems. Losing a job, however, is associated with a stronger increase in the risk of having significant mental health problems. The same report mentions loss of social status and reduced income as two of the main reasons behind this increase (FHI, 2011).

Age and gender

International studies have shown that the prevalence of mental problems is higher among young adults compared to the elderly. The older population report less issues in general with their mental health despite reporting a less sense of mastery and accomplishment. One factor that may explain the negative relationship between frequency of reported mental health disorders and increasing age in Norway is the fact that aging in Norway is relatively less challenging than in other countries. However, the study expressed a fear of selection bias for the older age groups. They fear that only the healthiest of the elders are able to respond. This can lead to the results showing less mental health problems in this age group than what the unbiased data would have shown (FHI, 2011).

There are significant differences in the occurrence of mental health disorders between men and women. According to the study, women in the 16-24 age group are almost twice as likely to report significant mental health problems compared to men. A considerable amount of the women in this age group report a low sense of mastery. Additionally, the proportion of women that are prescribed medicine to relieve these issues is higher, with older women being more likely to take prescription drugs (FHI, 2011).

Singlehood and separation

Living in singlehood has been found to be associated with poor mental health, which may be due to the lack of social support that comes with being in a relationship. Meanwhile, being in a relationship or marriage has a positive effect on mental health (Kiecolt-Glaser & Newton, 2001). However, separation and divorcement increase the risk of having mental health problems (Næss et al., 2007; Amato & James 2010).
The causal effect for these two factors is difficult to ascertain. It may be that people with mental health problems are less likely to establish or sustain relationships. Therefore, mental health problems may be the cause of singlehood or separation, and not the other way around.

2.3 Previous research

In this section we will go through some of the recent Norwegian life quality and mental health research. Afterwards, we will approach some research about mental health during recessions in other countries, and a survey done during the first part of the lockdown in the US. In the end of the chapter, we will summarize the results for the factors in our research question - gender, age, education, economic situation, singlehood, and unemployment.

Recent history of Norwegian life quality and mental health research

In 2011, FHI did a condition report on Norwegian mental health based on data from the living condition survey done by Statistisk sentralbyrå (SSB)[4] in 2008. The survey contained questions about health, care, and social contact. It included 25 questions about the respondent's subjective opinion about their own mental health from the Hopkins Symptom Checklist (HSCL-25)[5]. The respondents answer the questions by giving a score of 1 to 4, with 1 being "not troubled" and 4 being "very troubled". Once all the questions are answered, the respondent receives an average score. The threshold average score for HSCL-25 is 1.75. If the respondent receives a score that is higher than the threshold score, he or she is defined as having considerable mental health problems (FHI, 2011).

The condition report by FHI in 2011 was the last report to go in depth on explanatory factors that could explain the nationwide state of mental health in Norway. In later years, the way mental health has been researched has been through life quality surveys in which mental health has received less attention. Instead, more focus has been put on subjective life quality, which in short, is about how people experience their lives. It includes the respondent's assessment of their relationships, economy, work-situation, sense of mastery and meaning, and positive and negative feelings. Many of these factors are also considered relevant for mental health, as seen in the previous section. The subjective life quality therefore partly overlaps with mental health (FHI, 2020).

Up until recently, surveys that have measured life quality have been conducted inconsistently. In 2017 the government introduced a new strategy which emphasized the importance of measuring life quality consistently and use it as a tool in the task of improving the nation's mental health (Regjeringen, 2017). In 2018 FHI and the Norwegian Directorate of Health (HDIR)[6] published their recommendation for a new measuring system for life quality. It included a minimum list of questions to be included in any life quality survey. However, this list did not include HSCL-5 for measuring mental health problems (FHI & Helsedirektoratet, 2018). The difference between the HSCL-5 method and the HSCL-25 method, is that the former only contains five questions and

[4] Hereby referred to as SSB
[5] Hereby referred to as HSCL-25
[6] Hereby referred to as HDIR

has a threshold score of 2, compared to 1.75 in the HSCL-25. FHI pointed out in their 2019 life quality report that including HSCL-5 in the minimum list would be an improvement (FHI, 2020). In the 2020 life quality report from SSB they included the HSCL-5 questionnaire in their survey, but they did not explicitly model for it. In other words, HSCL-5 was just an x-variable in their study, not the y-variable like in ours (SSB, 2020).

Condition report for mental health in Norway, 2011 - FHI

We will now look further at the aforementioned report by FHI from 2011 on the condition of mental health in Norway. The report used data gathered from the living condition survey done by SSB in 2008. Due to the fact that the financial crisis is not mentioned once in the entire report, we presume that the survey was conducted before the financial crisis hit in the fall of 2008. It was a nationwide representative survey, in which approximately 10 000 individuals were picked from SSB's demography- and population database called BEBAS. They achieved a 50% response rate, meaning that the final dataset consisted of about 5 000 Norwegians over the age of 16. The survey was conducted with a combination of a questionnaire and a personal interview. Although the sample picked from the database was representative for the entire population, FHI believe that the nationwide degree of mental health problems was, in reality, higher than what they found. The reason for this is that people in risk exposed groups may be averse or hesitant to participate in health-related surveys. This is also known as a non-response error, which is one of the forms of sampling errors (Investopedia, 2021). On the other hand, some of the people who actually did answer the questionnaire, may have overestimated how bad they are actually doing, which might create false positives in the results. Despite this, FHI believes that the underestimation, due to some of the risk exposed group refraining from participating in the survey, trumps the false positives (FHI, 2011).

FHI used the HSCL-25 questionnaire to measure mental health problems. In addition to HSCL-25, they also used a shorter questionnaire known as MHI-5 which is a part of a questionnaire created by Ware (Ware et al., 1993;2000). They used the average score for these two questionnaires and compared it to the average threshold values of 1.75 and 56, respectively. While the respondents are defined as having considerable mental health problems if they scores above the score of 1.75 in the HSCL-25, they have to score below 56 in the MHI-5 to receive the same definition.

Using these methods are not as precise as conducting clinical interviews, but they do have a fairly good ability for predicting mental health disorders. Research has shown that between 50-60% of those with an average score above the threshold value for HSCL-25 qualified for one or more mental disorders after clinical interviews (Derogatis et al., 1974; Sandanger et al., 1998;1999). The survey also included a series of questions estimating lifetime occurrence of severe depression. Using HSCL-25, FHI were able to predict 67% of the lifetime occurrences of severe depression, while the MHI-5 was able to predict 76%.

FHI argues that using such predictors is an adequate way of studying consequences on mental health due to social and economic factors. They would, however, not be satisfactory from a medical view (FHI, 2011).

Table 1 & 2: FHI 2011 - Percentages scoring HSCL-25>1.75 and MHI<56 for gender and age.

HSCL-25 > 1,75 - percentage after gender and age				
		Men	Women	Total
Age	16-24	6,8	24,0	16,5
	25-44	9,5	11,2	10,4
	45-64	8,1	11,6	9,9
	65-74	4,8	7,4	6,1
	75+	5,4	11,6	8,7
Total		7,8	12,4	10,2

MHI-5 < 56 - percentage after gender and age				
		Men	Women	Total
Age	16-24	5,2	12,4	9,2
	25-44	6,4	6,9	6,7
	45-64	5,7	6,0	5,8
	65-74	2,6	3,5	3,0
	75+	5,8	9,2	7,7
Total		5,5	7	6,3

Table 1 & 2 show that 10.2% of the respondents scored above the HSCL-25 threshold value, and 6.3% scored below the MHI-5 threshold value. The share of respondents defined as having considerable mental health problems were higher for women than men for all age groups. The share decreased with higher age, but it increased again above the age of 75. The most exposed group were women between 16 and 24 years, as seen in both tables.

Table 3 shows the odds ratios (OR)[7] for having considerable mental health problems as well as for having experienced severe depression for different explanatory factors. Age and gender are not included as explanatory factors in the tables, but they have been controlled for. However, the explanatory factors included in the table have not been controlled for each other. All the OR's are statistically significant. Table 3 shows that having serious economic problems is associated

[7] Hereby referred to as OR

with an OR of 10.48 for HSCL-25 > 1.75 and 9.7 for MHI-5 < 56. This means that someone who has experienced severe economic problems in the last year is 10.48 and 9.7 times more likely to have considerable mental health problems compared to someone who has not. Being below the poverty line, however, gives an OR of 2.19 and 2.32. This indicates that the impact of suffering a burdensome life event during the last year, such as severe economic problems, is more impactful than already being in a less fortunate life situation. Burdensome life events seem to have a high OR for having considerable mental health problems in general. We do however see that low social support, which falls under the life situation category, also has a high OR of 4.06 and 3.89, respectively. Those living alone had an OR of 1.98 and 2.58. This is consistent with the fact that 22.3% of those who were defined as having considerable mental health problems stated that they did not have someone to confide in. Unemployment is an explanatory factor that has been divided into both categories. The ones that have become unemployed or have searched for work for more than a month without success in the past year had an OR of 6.66 and 6.0 (FHI, 2011).

Table 3: FHI 2011 - Odds ratio for health results.

	Odds ratio for health results			
Burdensome life event occurences in the last year	Prevalence in %	HSCL-25 > 1,75	MHI-5 < 56	Severe depression (in lifetime)
Two or more negative life event	22,30	4,60	4,91	3,24
Severe economical problems	5,50	10,48	9,70	6,87
You have been separated because of problems in your marriage/cohabitation	2,70	3,97	5,88	3,36
You have become unemployed or have searched for work in more than a month without success	3,70	6,00	6,66	4,28
You have been dismissed from your employment	1,50	5,08	5,54	3,89
Experienced violence	2,50	3,52	4,37	2,02
Used narcotics	2,70	5,43	4,75	3,40
Life situation				
Low social support	9,30	4,06	3,89	2,15
Chronic illness	40,20	2,38	2,12	2,08
Chronic pain	26,70	2,99	2,40	2,34
Unemployed the last 3 months	2,40	3,55	3,37	3,36
Under the poverty line	7,40	2,19	2,32	1,51
Living alone	25,90	1,91	2,58	1,53

Life quality report, 2019 - FHI

The life quality report from 2019 used data from public health surveys (FHUS) done in the counties of Hedmark, Østfold, Finnmark, Troms and Agder in 2019 (FHI, 2020). In addition, the dataset included a pilot survey done in Hallingdal. The surveys were self-administered web surveys, except for in Hedmark where the web survey was complemented with a postal version as a consideration for the oldest age groups. The questionnaires consisted of the 23 questions on the minimum list from the new measuring system from 2018, as well as additional questions about health and the local community. 2 of the 23 questions had a focus on mental health, and are called PHQ-2 (FHI, 2020). These two questions have not been commonly used in Norwegian research – which makes the report difficult to compare with other research.

There were not many findings regarding mental health due to it not being a main focus in the report. They did find, however, that those with a partner reported less mental health problems. Mental health problems decreased with higher age, but in contrast to the FHI 2011 report, the trend did not shift for the oldest age group. This may have been due to the fact that only the healthiest of the elders were likely to be able to complete the survey, which would make the data somewhat skewed for the oldest age groups. This has been a recurring problem in these types of research according to FHI (FHI 2020).

Life quality report, 2020 – SSB

In March 2020 SSB conducted a nationwide life quality survey, with a sample of 40 000 individuals above the age of 18. They achieved a 44% response rate, with non-responses being more prevalent for those above 80 years, and those without education. Once again, it is likely that the healthiest in the age group responded.

The survey was conducted between March 9th and 29th. Since the COVID-19 measures were put in motion on March 12th in Norway, some of the answers came after the measures were initiated. In fact, only 25% of the respondents answered before the 12th. The timing of the survey makes interpreting the results somewhat complicated. For the respondents that answered after March 12th, some of them might have answered the questions with their current lockdown-affected situation in mind, while others may have answered thinking of their general mental health over time.

SSB reported that worse mental health was more prevalent for those who answered after March 12th. Nevertheless, they argue that the timing of the survey is unlikely to change the differences between the different subgroups, such as age- and socioeconomic groups (SSB, 2020).

As in the previous life quality report, mental health was not the main focus. They did include HSCL-5 in their survey, but they did not model for it like we did. They instead used it as an x-variable for subjective life quality. They did, however, find that the age group 18-24 scored the lowest when it came to satisfaction with their mental health. This might be due to the fact that respondents aged 18-24 are also the least satisfied with their own economic situation compared to the other age groups. Economic situation, as mentioned earlier, is an explanatory factor for having mental health problems. They also found that those without a college education reported lower satisfaction with their mental health than those with. This was also the case for those who were unemployed or on disability benefits (SSB, 2020).

Previous research on mental health during economic recessions

The human cost of economic recessions has been considered to be significant, with it particularly applying to vulnerable groups of people (Zivin et al. 2010). Mental health problems were even more prevalent in those who were struggling before the crisis occurred (Alonso, 2004). As a result of the decline in global trade and economic growth that followed the financial crisis in 2008, unemployment rates increased considerably. Almost half of the population in Europe reported knowing someone who had lost their job as a direct result of the crisis (European Commission, 2013).

There are limited studies that compare the change in mental wellbeing before and after a recession. A longitudinal study from Greece showed that self-perceived mental health was negatively affected by the increase in unemployment rates during the years of the recession from 2008 to 2013 (Drydakis, 2015). Repeated cross-sectional studies from England and Spain showed that the recession led to an increase in the prevalence of mental distress, with it having a greater impact on men than women (Katikireddi et al., 2012, Bartoll et al., 2014). A study from Japan also concluded that a recession could be a direct reason for an increase in poor mental health for people across all socioeconomic ranks (Kondo et al., 2008). A longitudinal study from Iceland showed an increase in morbidity rates in the form of higher stress levels in the population after the recession compared to before. This was, however, only significant for women and had a higher impact on those who were unemployed (Hauksdóttir et al., 2013). In Spain, results from a study showed that the risk of suffering from depression during a recession was almost three times the risk compared to before the recession (Gili et al., 2013).

Findings from different studies suggest that because of economic recessions, men and women are affected differently in terms of mental health. Typically, studies have found that men are more vulnerable to mental health problems during and after economic recessions, due to men being more involved in the affected labor markets. However, in a research paper by Dagher, Chen and Thomas from 2015, they discussed that this might not be the case anymore because of the increased involvement of women in the labor market (Dagher, Chen and Thomas, 2015). In fact, they found that both genders had a lower probability of being diagnosed with depression, during and after the economic recession. They argue that this was because people had more time to be with friends and family, and more time for leisure. However, they did find that females had an increased probability of being diagnosed with anxiety after the economic recession. Women have consistently been found to have increased probability of having anxiety disorders compared to men (McLean et al., 2011).

The Impact of the Coronavirus Lockdown on Mental Health: Evidence from the US, 2020 - HCEO.

Human Capital and Economic Opportunity Global Working Group (HCEO)[8] conducted a US study about the impact of the COVID-19 lockdown on mental health. They used geographically representative survey data collected in March and April 2020 to study the impact of state-wide stay-at-home orders on mental health. They used the WHO 5-question module to measure mental health, and they had 8 003 respondents over the age of 18.

Unlike the previous research we have looked at in this chapter, HCEO provided a detailed overview of their model. They used an ordinary least squares (OLS)[9] regression with a mental health score as the y-variable. The x-variables were dummy variables for lockdown (in April), female, 4

[8] Hereby referred to as HCEO
[9] Hereby referred to as OLS

age groups, college degree, the respondent being single. The last variable was a discrete variable for the respondent's household income (Adams-Prassl et al., 2020).

The HCEO study found that respondents from states with lockdown measures had worse mental health in general. They did a placebo test to make sure the respondents in the states with stay-at-home orders did not have a systematically different baseline score. They found that the impact from the lockdown orders on mental health was completely driven by women. The impact on men was almost zero and deemed insignificant. Another research paper pointed at increased childcare as a possible explanation for the mental health gender gap observed in the HCEO study. This paper found that the increase in childcare, due to the measures, affected mothers the most. This partly came at the expense of leisure and was found to lead to a larger welfare loss for women (Alon et al, 2020). The HCEO study also found that an increase in household income had a positive impact on mental health. The same was true for having a college degree, while singlehood had a negative impact.

2.4 Summary and discussion about previous research

The FHI 2011 report did, similar to us, look at how different explanatory factors affected having mental health problems. For each explanatory variable, the 2011 report only controlled for age and gender. Our model, however, controlled for the other explanatory variables as well. One can question the validity of their results, as there is likely to be biased and inconsistent estimates due to omitted variable bias (OVB)[10], which is one source of endogeneity. Nonetheless, it might be the most relevant study for us to compare our results with, as our models had some similar explanatory factors. Both of our studies found that women were more exposed to mental health problems and that it was more prevalent amongst the younger age groups. Another similarity between our findings is that those having economic problems and those who were unemployed were more likely to have mental health problems.

[10] Hereby referred to as OVB

Although our models can be comparable in some ways, it is important to note that our datasets were collected at two completely different times. While the 2011 FHI report was conducted during relatively normal times, our study was done during the COVID-19 pandemic. In the results part of the thesis, we will compare the OR's on 2 of our variables with 2 of the OR's for the FHI 2011 report's variables.

Unlike us, neither of the life quality reports made by FHI in 2019 and SSB in 2020 modeled mental health problems explicitly. One similarity between our findings and theirs, is that the younger age groups are those who are suffering the most. While the FHI 2019 report reports this explicitly, the SSB 2020 report found that the younger age groups have the least satisfaction with their own mental health. The FHI 2019 differs when it comes to the oldest age groups. Our model in addition to SSB 2020 and FHI 2011, found that the trend of decreased mental health with age switches in the oldest age group, as the share of the oldest age group suffering is relatively higher than the previous age group.

In both the FHI report from 2019 and SSB report from 2020 they found that those with a partner had less mental health problems. This can perhaps be compared with our finding for those being single having higher probability of having mental health problems.
SSB found that those without a college degree had lower satisfaction with their mental health. This can be somewhat comparable to our findings, as those with a higher education had a lower probability of having mental health problems. Our findings were also somewhat similar in regard to those unemployed. While those unemployed in the SSB 2020 were less satisfied with their mental health, being unemployed was associated with a higher probability of having mental health problems in our findings.

Research for mental health during economic recessions found that men generally have been found to be the most affected, but that relation has been questioned by other research. The effect of economic recessions seems to be very context dependent, and since COVID-19 created such a unique type of recession our results might differ. The studies that found men to be more affected during economic recessions pointed at more men losing their jobs as a possible reason for this. This was also the case in Norway during the pandemic, as more men lost their jobs.

Despite this, our results showed that women were more likely to have mental health problems during the pandemic. A reason for this may be that the mental burden from the pandemic itself trumped the effect of becoming unemployed. It can also be due to the fact that women have consistently been found to have an increased probability of having anxiety disorders compared to men (McLean et al., 2011).

The HCEO study modeled mental health explicitly, but with some differences to our model. First off, instead of having a threshold value for mental health problems as the dependent variable, they used mental health scores. Secondly, they used a different questionnaire than us, and so their variables were different. Lastly, they used OLS regression contrary to our logistic regression, and their research question was also different. They primarily wanted to see how the lockdown measures affected the mental health scores, while we wanted to see how other explanatory factors play on the probability of having mental health problems during COVID-19. Their study did, however, find that women were more exposed during the pandemic. Having a higher education, and having a partner decreased the probability of having mental health problems.

Perhaps the biggest challenge for comparing our results with theirs is the social context. The measures in Norway in November and December 2020 were different from the stay-at-home orders in the US in March and April 2020. In the US, the orders differed from state to state, and some states even had no measures in this period. The stay-at-home orders meant that both work and school were carried out from home - or not at all. Meanwhile, measures were similar for most of Norway. Kindergartens, primary schools, and junior-high schools were open during our data period. This lightens the burden in terms of childcare for parents in Norway compared to the US.

3 Background

3.1 The cost of mental health problems

Mental health problems affect the economy negatively for various reasons. One way of calculating the cost of the problems is by attempting to calculate the productivity loss it causes. Norwegian Labor and Welfare Administration (NAV)[11] uses the "Disability-adjusted life year" (DALY)[12] as a measure for the working time lost or whether the person has died earlier than expected due to an illness. Briefly explained, DALY is the number of years an individual is able to work given that he is healthy, subtracted with the number of years he has not been able to work due to illnesses throughout his or her life. In 2015, the combined number of years lost due to mental health problems was 169 369 years, making it the second largest group after people with cancer (Helsedirektoratet, 2019). Based on these numbers, mental health problems are one of the main reasons for not being able to work the full period in which a person is expected to.

DALY, however, is not a monetary value, and there is no easy way of quantifying its worth. HDIR has proposed the value to be NOK 1.138 million. If we use the proposed value of one DALY, the cost of all of the years lost due to mental health problems would correspond to a total of NOK 192.7 billion in 2015 alone. Another way of estimating the cost of mental health is by calculating the cost of treatment for mental health patients. They were the most expensive patients to treat with NOK 37.2 billion in 2015. This accounted for 19.6% of the total health care expenditures in Norway that year. By comparison, cancer treatment and treatment for musculoskeletal issues amounted to NOK 17.9 billion and NOK 17.5 billion, respectively (Helsedirektoratet, 2019).

We mentioned earlier that one of the main reasons for not being able to work is problems regarding mental health. In 2015, mental health was the second most frequent cause of being temporarily absent from work with 19.8% of all cases. This results in reduced tax income for the government in the period in which the individual is absent. For cases in which the individual is permanently laid off due to mental health problems, the government also faces increased cost in the form of social benefit payments. In the same year, 35.3% of all cases of disability pensions were

[11] Hereby referred to as NAV
[12] Hereby referred to as DALY

due to mental health problems. The total economic cost of being temporary or permanently absent from work was NOK 48.3 billion, in 2015. In total, the cumulative cost of DALY, the cost of treatment and the productivity loss makes mental health problems the most expensive out of all diseases (Helsedirektoratet, 2019).

3.2 The Norwegian system

Now, what role does the Norwegian system play in what we covered in the previous section? Compared to other OECD countries, Norway ranks among the lowest when it comes to unemployment rate. Norway also has the highest spending on education, with 8% of the GDP spent on education in 2019. Despite having a healthy economy and a high standard of living, Norway ranks on top of the list of sickness absence, with around 7% of the entire workforce being on sick leave at any given point of time (OECD, 2013). In 2015, around 20% of those on sick leave stated mental health problems as the cause (Helsedirektoratet, 2019). In comparison to other OECD countries, Norway also has the highest mental health-related unemployment gap both when it comes to moderate and severe mental health problems. Moderate problems had a three-fold unemployment rate and severe problems a nine-fold unemployment rate compared to those without these types of problems (OECD, 2013).

Although the Norwegian economy has grown substantially and the unemployment rate has fallen since the 90's, the unemployment rate among those with mental problems has increased by three percentage points. This negative growth is the second largest among the OECD countries (OECD, 2013). Two studies have found evidence that this negative growth in the employment rate among those who suffer from mental problems may be due to immigrating. Workers immigrating to Norway have displaced low-wage earners, who often were workers with mental problems (Jean et al., 2007; Bratsberg et al., 2012). The report made by OECD highlights the prevalence of mental health problems in people who are unemployed. More than every second unemployed Norwegian suffers from severe or moderate mental health problems (OECD, 2013).

There are many factors that contribute to the high degree of sick leave due to mental health problems. One of the factors is the generous compensation system that is an integral part of the Norwegian welfare state. During a normal, pandemic-free situation, firms are obliged to cover the wage costs for the first 16 days of absence. If the absence goes beyond those 16 days, the financial obligation is moved from the employer to the government – offering a compensation of 100% of your income for a year, unless the annual wage is above the countrywide mean wage. Seeing as your economy is untouched during your sick leave, this could reduce the financial incentive to return to work. Financial stability as an explanatory factor, has been linked with less mental health problems, which the compensation system ensures. However, since being unemployed has consistently been associated with having worse mental health, the lack of financial incentive to return to work could be an unfortunate byproduct of the generous system. It might lead to people returning to employment later than when it would be mentally beneficial to do so.

In addition to the generous compensation system for people out of work, Norway also has a strong vocation integration focus (OECD, 2010a). Norway has the strongest integration approach of the OECD countries, with a variety of vocational rehabilitation support programs through NAV, which can be applied at any time. The OECD report from 2013 states that the high number of people who are out of the labor force due to mental health problems is not due to lack of support structures or integration policies. The problems may be more related to the way in which these measures are regulated, implemented, evaluated, and monitored (OECD, 2013).

3.3 Life during COVID-19 in Norway

In early March, the government introduced measures to counter the rapid spread of the COVID-19 disease. Workplaces, schools, movie theaters, pubs, and other places most of us considered as essential parts of our daily lives, shut down overnight. This was the starting point of a long period of self-isolation and a massive reduction in economic activity. In many ways, the stage was set for a spike in mental health problems.

As the companies were forced to close down either due to lockdown measures or loss of revenue, many people were without work. NAV reported that 300 000 people were fully unemployed following the first lockdown in March. If they include the amount of people put on furlough and other NAV initiatives, 433 000 people were out of work, equivalent to 15% of the workforce (NAV, 2020).

For many people, the workplace is not only a place that is used to generate income, but additionally a social arena consisting of close connection with your colleagues and personal relationships. In fact, after household and family, Norwegians rank their workplaces on top of the list of things that they value highly when it comes to their own mental health (Rådet for psykisk helse, 2020). Losing your job during the pandemic comes with several consequences. One consequence is the reduced income that comes with not working, and another consequence is the mental impact that comes with not being able to go work, seeing your coworkers, and being isolated in your own home.

Now, which workplaces are affected? A study made by Alstadsæter et al. in 2020 shows that 70% of those who were working in firms that were subject to a forced stoppage in activity in the first lockdown, were put on furlough during the period between March 16th and April 19th. The same was the case for approximately 40% of the people who had jobs that were implicitly banned through distancing restrictions. Workers in businesses that were imposed restrictions, which prevented customers from using their services, saw similar numbers (Alstadsæter et al., 2020).

The study also highlights the difference between men and women. According to the study, women are more likely to have a job that is described as requiring physical proximity.
Due to an overrepresentation of women with occupations requiring physical closeness, such as hairdressers, receptionists, and waitresses, the first week of the crisis affected mostly women. The study further reveals that while physical proximity was a driving factor in the beginning of the lockdown, the importance of physical proximity was significantly reduced after just a few days. While women are overrepresented in the public sector, men are overrepresented in the private sector. As the economic crisis spread, the private sector became more exposed to layoffs.

When the lockdown measures were imposed, women initially bore the brunt of the layoff. This initial reaction was more than offset after just a few days, with the exposure for being laid off becoming more skewed towards men. The long-term effects of the pandemic on the gender differences in the labor market are uncertain. The job market will likely become more challenging as a consequence of the pandemic, and according to a report by Bufdir, women will have a disadvantage compared to men (Bufdir, 2020).

Alstadsæter et al. also found that the difference in exposure of layoffs in the private sector was associated with having children; women with young children have a higher exposure than men with young children. When children are taken out of the equation, men and women actually have the same exposure for being laid off in the private sector, but since men are overrepresented, more men are laid off (Alstadsæter et al., 2020). The higher exposure for women with children at home can be associated with women having had a larger responsibility for following up and helping the children with their schoolwork (Nergaard 2020). Another research has, however, shown that both men and women reported a more equal distribution of childcare. In contrast to the previous research, this indicates that the pandemic has actually led to some decrease in the gender differences in terms of childcare that existed pre-COVID-19 (AFI, 2020).

3.4 Development of mental health problems before and during COVID-19

SSB’s life quality report from March 2020 found that about 18% scored above the threshold score of 2 for having considerable mental health problems, while the FHI report in November and December stated that 16.8% scored the same. FHI mention that the amount of people having considerable mental health problems has stayed fairly stable between 9 and 12% for the population as a whole the last 20 years. They believe that the higher percentage in March as well as in November and December reflects the pandemic and the measures it brought (FHI, Nov/Des 2020) This development can be seen in figure 1.

Figure 1: FHI 2020 - Occurrence of considerable mental health problems

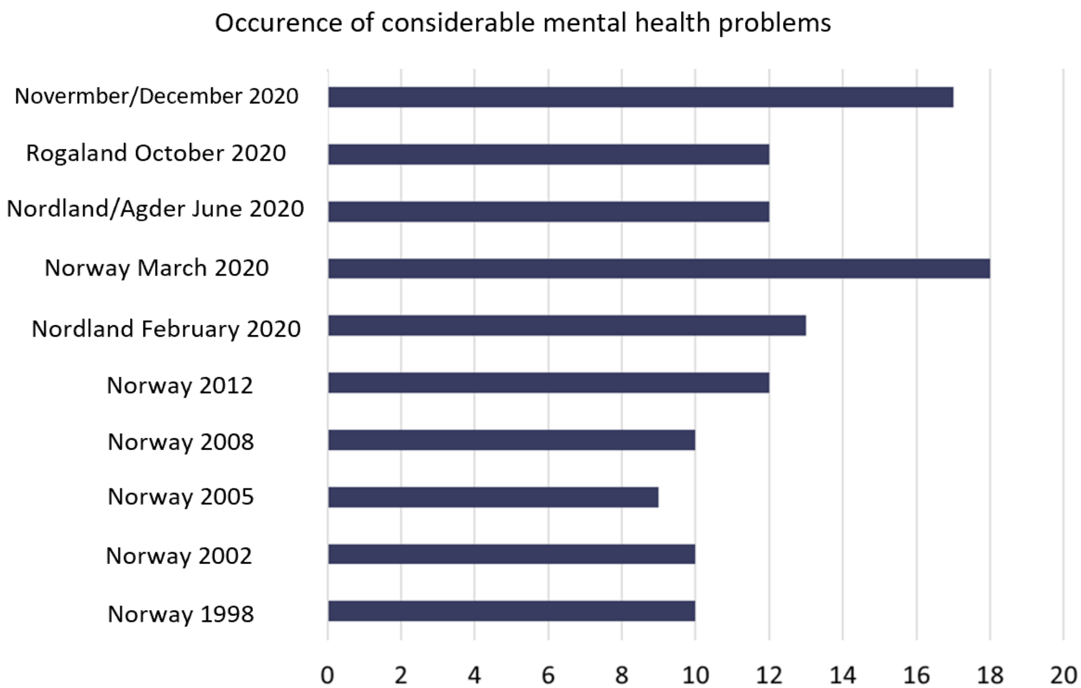


Figure 2: FHI 2020 - HSCL scores at three different points in time

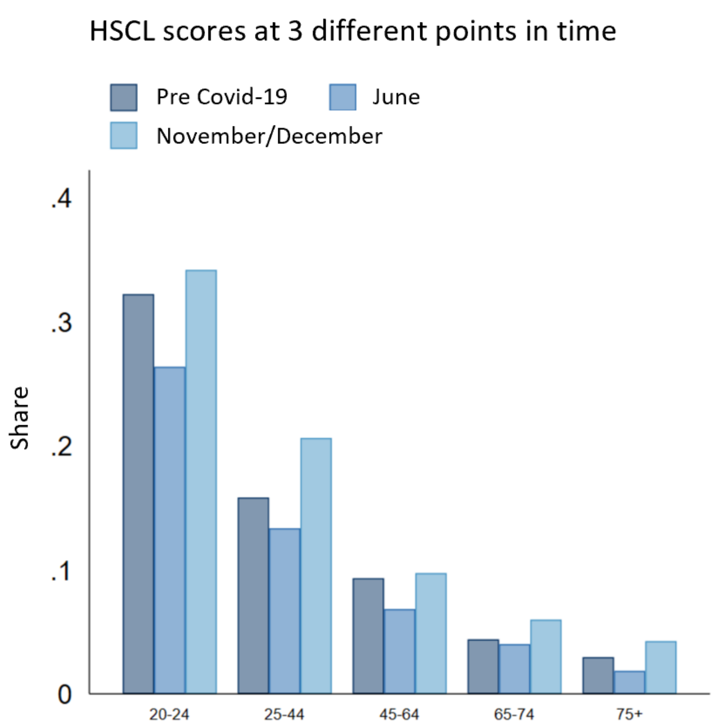


Figure 2 specifically shows the percentage of five different age groups struggling with considerable mental health problems, at three different points in time. This was done by using the HSCL-5 questionnaire. In June there were a lot fewer cases of individuals with considerable mental health problems than before the pandemic, for all age groups. This can be explained by the significant boost in morale that came with the increased freedom to be outside, which was the case for people in all age groups, except for the respondents above the age of 65. Due to the fact that those above this age were in the risk group, they may not have experienced the same degree of freedom. FHI argue that another reason for the lower share of people struggling may be because it was summertime. They also state that it might be due to a lower sample size in June.

The increased number of cases of COVID-19 during the fall forced the government to initiate another lockdown. Figure 2 shows us that the new lockdown caused a spike in the number of cases of considerable mental health problems, especially in the younger age groups. For all age groups, the percentage of people with considerable mental health problems went above the percentages pre-COVID-19. The fact that the society had to close down again, when many people may have thought that the crisis was over, may have been one of the reasons for this.

4 Empirical strategy

In this chapter we will discuss the form of estimation model we chose to use. We will then present the model that we used in the results part of the thesis, before we discuss its limitations and possible challenges.

4.1 Choice of model form - logistic regression with multiple regressors

Our thesis aims to look at what part different explanatory variables play on the probability of having considerable mental health problems. The dependent variable in our model is a binary variable. In other words, y_i can only take on two values: 0 or 1. The respondent has the value of 1 if they score above the HSCL-5 threshold score of 2 and is thus defined as having considerable mental health problems. If the respondent scores below the threshold score of 2, they are not defined as such, and therefore have the value of 0.

We could have used the linear probability model (LPM)[13], which is an example of a binary regression model. However, the main drawback of using the LPM is that the predicted probability of having Y = 1 can take on values outside of [0,1]. This is illogical, as it is not possible to have probability beneath 0 or above 1. This fundamental issue with LPM cannot be solved unless we place restrictions on the beta values, which would be counterproductive. Taking this into account, we instead decided to use a logistic model - also known as logit. We could also have used a probit regression model which is very similar to logit, however, we have more experience with the logit model, and it is generally agreed to be easier to interpret (Dustan, 2010).

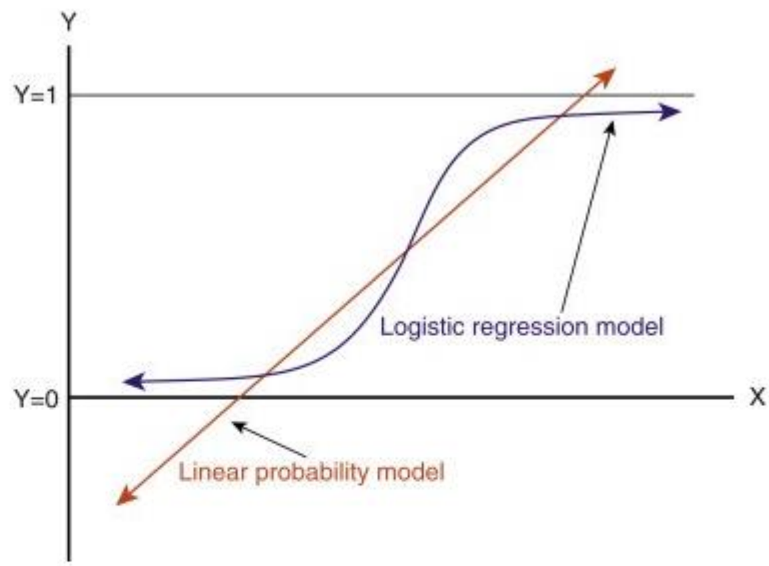
Logistic regression models the probability for Y to be equal to 1, given one or multiple explanatory variables. This is shown in equation (1).

$$\hat{y} = \Pr\ (Y = 1 | X_1, X_2, \dots, X_k) = F(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k)}} \tag{1}$$

[13] Hereby referred to as LPM

As we can see from equation (1), the probability will now always be between 0 and 1. This can also be seen in the graphical illustration of the logistic regression model and the linear probability in figure 3 below.

Figure 3: Towards Data Science 2019 - Logistic regression and linear probability model



When running a logit model in Stata, the coefficient β would be in the form of log-odds. The log-odds value is not easily interpreted. However, by seeing if the value is positive or negative, we are able to tell in which way the relation between the x- and y-variable goes. A positive log-odds would mean that there is a positive relationship between the explanatory variable and the dependent variable. In other words, it would indicate that with an increase in the explanatory variable, the probability of Y = 1 would increase. The opposite would be the case for a negative log-odds. As log-odds leave something to be desired in terms of interpretation, we instead use OR's and margins. To obtain an OR value, one can take the antilogarithm of the log-odds. See equation (2).

$$\text{Odds ratio (OR)} = e^{\beta} \qquad (2)$$

OR's tell us how much the odds is increased for Y = 1 with a one unit increase in the associated x-variable. An OR above 1 means that the odds for Y = 1 will increase, while an OR below 1 would mean that the odds would decrease, after one unit increase on the x-variable. In the FHI report from 2011 they found that an occurrence of severe economic problems during the past year was associated with an OR of 10.48. This can be interpreted as the odds for having considerable mental health problems was 10.48 times higher for this group (FHI, 2011). We have included OR's in our model to be able to compare some of our findings with the findings from the FHI 2011 report. To answer the research question, we use the Stata command *margins* to find the marginal effect on a unit increase of x on ŷ. In other words, the marginal effect makes us able to determine how much more likely respondents are to have Y = 1 given a change in the x-variable.

For x-variables that are dummies, by using margins, we see the probability of Y = 1 when the dummy has the value of 1. For discrete x-variables the effect would be from a one-unit change. This interpretation might not be logical for some variables. In our model all the variables are dummies except for the one variable for the number of children under the age of 18 the respondent has in their care ("childund18"). We could use the *mfx* command instead of the *margins* command to find the marginal effect for a change in x for the average person, but the average person would have approximately 1.65 children under the age of 18 in their care. Ultimately, we are content with interpreting the marginal effect from going from 0 to 1 child under the age of 18 in their care, and we thus refrain from using the *mfx* command.

4.2 Our model

Our Benchmark model is shown in equation (3).

$$Probability\ of\ HSCL\ score > 2 = \frac{1}{1+e^{-(\beta_0+\beta_1 X_1+\beta_2 X_2+\cdots+\beta_{11} X_{11})}} \quad (3)$$

The x-variables can be seen in table 4. Each variable is further explained in chapter 5.

Table 4: X-variables in our Benchmark model

Variable	Variable Name	Description
X_1	oslobergen	Dummy variable equal to 1 if respondent lives in either Oslo or Bergen
X_2	female	Dummy variable equal to 1 if respondent is female
X_3	higheredu	Dummy variable equal to 1 if respondent have completed a college degree
X_4	single	Dummy variable equal to 1 if respondent is single
X_5	age18_24	Dummy variable equal to 1 if respondent is between 18 and 24 years old
X_6	age25_44	Dummy variable equal to 1 if respondent is between 25 and 44 years old
X_7	age45_64	Dummy variable equal to 1 if respondent is between 45 and 64 years old
X_8	age75over	Dummy variable equal to 1 if respondent is 75 years old or older
X_9	childund18	Numeric variable for number of children under the age of 18 in respondents care
X_{10}	challeco	Dummy variable equal to 1 if respondent consider their personal economy challenging
X_{11}	withoutwork	Dummy variable equal to 1 if respondent is completely without work

Additionally, we have three more models that consist of the variables from the Benchmark model. Each model also includes their own interaction variable. The three interactions are shown in table 5.

Table 5: Extra x-variables in model 2, 3 and 4.

X_{12} (model 2)	female_age18_24	Interaction between female and age18_24
X_{12} (model 3)	female_challeco	Interaction between female and challeco
X_{12} (model 4)	age18_24_challeco	Interaction between age18_24 and challeco

When adding interactions to a model it is recommended to proceed with some caution. Adding many interactions in the hunt for p-values might cause multiplicity. If we test too many, we would eventually get some results that would be statistically significant, even if there was in fact no underlying effect. In other words, by testing too many variables, we could find coincidental results. Having too many interactions in the same model could also create problems with multi-collinearity (Vach, 2013). By adding interactions, we attempt to get a deeper understanding into some of the groups that have consistently been prone to having considerable mental health problems, according to the research we covered in chapter 2. The three groups we look at are those aged between 18 and 24, the ones with economic challenges, and females.

4.3 Multicollinearity

A high correlation between two or more of the x-variables leads to less precise coefficients and weakens the reliability of the p-values. It can also make coefficients more sensitive to any changes in the model. The term for this problem is multicollinearity (Frost, 2017). An example of this could be the variable "higheredu" in our model. This variable might be linked with another variable in our model, which is the economic variable "challeco". This is due to the fact that generally, those with a higher education are likely to have a more stable economy. We can test for multicollinearity by finding the Variance Inflation Factor (VIF)[14] in Stata, which measures the correlation between the x-variables. A VIF score of 1 means that there is no correlation between the x-variable in question and the other x-variables in the model. A VIF score between 1 and 5 is defined as a moderate correlation, while a VIF score above 5 is defined as high correlation and means that the coefficients are poorly estimated (Glen, 2015). The VIF scores for the variables in our models are showcased in table 6. None of the variables are above the critical VIF score of 5. "Higheredu" only had a VIF score of 1.15, which would indicate that there is only moderate multicollinearity linked with this variable. The Benchmark model had very low VIF scores in general, with the highest one being 1.39 for the age25_44 variable. However, interactions will innately have higher VIF scores as they will correlate with the original x-variables they are the interactions of. Even in the models that include an interaction, the VIF scores do not surpass the critical value of 5. Model 4 has the highest VIF scores with 3.10 and 3.33 for "female_age18_24" and "age18_24" respectively.

Due to the multicollinearity only being moderate in all four models, there is not enough reason to make any changes to them, especially since some higher multicollinearity is expected when including interaction variables. Out of the models that included an interaction, model 3 has the lowest VIF scores. Some researchers, however, consider a VIF score of 2.5 to be critical. If we were to adhere to their judgement, we would need to do something about model 4.

Table 6: VIF for model 1, 2, 3 and 4.

Benchmark model:	
Variable name	**VIF**
oslobergen	1,12
female	1,04
higheredu	1,15
single	1,18
age18_24	1,29
age25_44	1,39
age65_74	1,28
age75over	1,12
childund18	1,29
challeco	1,14
changeworksit	1,15
withoutwork	1,12

Model 2:	
Variable name	**VIF**
female_challeco	2,45
female	1,21
challeco	2,38
Model 3:	
Variable name	**VIF**
age18_24_challeco	1,50
age18_24	1,67
challeco	1,26
Model 4:	
Variable name	**VIF**
female_age18_24	3,10
female	1,10
age18_24	3,33

[14] Hereby referred to as VIF

The most extreme case of multicollinearity is called perfect multicollinearity. This means that the x-variable is the perfect linear combination of the other x-variables. To guard against this, we have excluded one of the variables for each category, e.g., one of the age groups. This excluded variable will become our reference variable. We will go through this process for all our dummy variables in the next chapter. Not doing this for all our dummy variables would result in perfect multicollinearity. In literature, this is referred to as falling into the dummy variable trap (Stock & Watson, 2014).

4.4 Endogeneity

Perhaps the biggest weakness of our models is the endogeneity problem. Endogeneity occurs when the x-variables in the model are affected by the other variables, even the y-variable. OVB, which is correlation between the x-variable and the error term, is a form of endogeneity. The error term contains all other factors that affect the y-variable, otherwise known as omitted variables. Another source of endogeneity is simultaneity bias. This occurs when the y-variable is not just caused by the x-variable, but also causes the x-variable. Both OVB and simultaneity bias weakens the internal validity of a model, as the regression might produce inconsistent and biased estimates (Stock & Watson, 2014).

Multiple of our variables might suffer from endogeneity. There is reason to believe that we have simultaneity bias when it comes to "higheredu" and our y-variable. Education seems to have a positive effect on mental health, as it gives both a feeling of mastery and accomplishment (Dalgard et al., 2007). At the same time, having considerable mental health problems can also affect the individuals' ability to complete higher education. In other words, the y-variable can also cause x. As mentioned in the previous section, "higheredu" and "challeco" can be somewhat linked with each other. This means that there could be a single omitted variable that would cause OVB for both of them. The respondent's parents' education could be such a variable. Research has found a relation between the parents' education and their children's. The personal economy of the respondent is also likely to be better if the parents have higher education (Dubow et al. 2009). The parents' education could be a factor affecting the probability of having considerable mental health problems. This would mean that the respondent's parents' education would be an omitted variable captured in the error term. If this would be the case, it would mean that both “higheredu” and “challeco” is correlated with the error term, and therefore suffer from endogeneity (Stock & Watson, 2014).

For the “challeco” variable there is also reason to believe that it can suffer from simultaneity bias. If you are suffering from considerable mental health problems you might need to seek treatment, which would come at a monetary expense. Although, in Norway you are exempt from the cost of certain health services, for the rest of the year once you have paid a total of NOK 2460 in user fees. Psychologist is one of these services (Helse Norge, 2021). This exemption would not cover alternative treatments and other possible costs in the process of treating your mental health problems. Mental health problems like depression could also cause people to not have the energy or will to make their own food, and therefore go for more expensive options like prepared meals and takeaway.

It also seems reasonable to believe that having considerable mental health problems could affect the respondent’s ability to work, and therefore might lead to unemployment. “Withoutwork” might therefore also suffer from simultaneity bias.

We have now talked about how a few of our variables suffer from endogeneity, but there is reason to believe that even more of them do. Endogeneity affects our ability to find conclusive causal relationships between our x-variables and the y-variable. Simultaneity bias makes it hard to know which way the causality goes, and OVB makes it hard to trust the estimates. Instrumental variables are sometimes used to deal with endogeneity, but this is unfortunately not possibly given the variables we have at our disposal.

The different explanatory factors for considerable mental health problems are, as we have seen, interlinked. Because of this, endogeneity will probably remain an issue for research on mental health problems until we have developed better models. This is dependent on further research on the explanatory factors as well as larger data sets. E.g., if our dataset had contained information about the respondent’s parents’ education, we may have been able to control for the correlation with “higheredu” and “challeco” and the OVB this created.

4.5 Goodness of fit tests

In Stata we used the Pearson and the Hosmer Lemeshow goodness of fit tests to see how well the model fit the data and whether the x-variables are specified well or not. Both tests indicate a good fit if their p-values are above 5%. For the Pearson test, none of our models satisfied this criterion. When it comes to the Hosmer Lemeshow test, only model 3 satisfied the criterion. For the output for the two tests, see table A1-4 in the Appendix. In addition to these two tests, we also used the Stata command *estat classification* which shows the percentage of observations the model classifies correctly.

Estat classification splits up the observations into two component groups: the observations it assumes the model predicts to have a positive outcome (Y = 1) and the ones it assumes the model predicts to have a negative outcome (Y = 0). It does so by using a cut-off probability point. The default is 0.5 probability. This means that respondents the model finds to have a 0.5 or higher probability of having considerable mental health problems will be put into a positive outcome group. However, our model is not comprehensive enough to measure such high probabilities for many of the respondents. The model output reflects this, as the most influential explanatory is "challeco" which gives approximately a 0.16 higher probability. With the model's probability outputs there will not be many respondents that will have over 0.5 probability. This means that the group the *estat classification* command assumes the model to predict having Y = 1 will be very small. The command is sensitive to the sizes of each component group and favors classification for the larger group (Stata, 2018). To assess the proficiency of our model more accurately we had to find the relevant probability cut-off point given the probabilities that our model produces. To do this we used the *lsens* command in Stata. We did this for each of the 4 models and found their respective probability cut-offs, see graph A5-A8 in the Appendix. We then used these probability cut-offs for the *estat classification* command for each model, instead of the default 0.5 probability. See table A9-A12 in the Appendix.

The results were similar for each of the models. However, Model 3 did once again stand out as the best model. For this model we used 0.1533768 as the probability cut-off. The model was able to accurately classify 68.95% of the observations defined as Y = 1 given the cut-off, which is also known as the model's sensitivity. The model was also able to accurately classify 69.76% of the ones defined as Y = 0, which is also known as specificity. In total, Model 3 was able to accurately classify 69.64% of the observations. However, this means the model predicts about 30% incorrectly. These results can be seen in table A11 in the Appendix.

In summary, Model 3 had the highest percentage of correctly classified observations. In addition, Model 3 was the only one to satisfy Hosmer Lemeshow goodness of fit test and had the lowest grade of multicollinearity. Based on these results, we will be using Model 3 to answer our research question. Model 3 also had the highest McFadden's Pseudo R^2, highest Cox & Snell R^2 and the highest Nagelkerke R^2, which we disclose in chapter 6.

5 Data

In this chapter we will describe the dataset we have used for our research. To start the chapter, we will present the dataset we received and discuss weaknesses. Afterwards, we will describe both the dependent variable and the explanatory variables in depth.

5.1 The dataset

Our goal is to study how some explanatory factors play on the probability of having considerable mental health problems. Our dataset was provided by FHI and was a part of a survey on life quality and mental health conducted between November 18th and December 4th 2020. A total of 58 000 Norwegians above the age of 18 from Oslo, Agder, Nordland and Vestland were invited to participate in the survey. In total 26 039 responded, which corresponds to a response rate of approximately 44.9%. The dataset separated Bergen from Vestland, in order to single out respondents from two big cities: Bergen and Oslo. These two cities had some stricter measures than the other regions included in the survey during the research period (FHI, Nov/Dec 2020).

The survey was a quantitative survey conducted online and took between 15-20 minutes to complete. It consisted of between 97 and 134 questions, depending on which answers you gave on some of the questions. The part of the survey that we received consisted of 12 of these questions. The questions which we used for our thesis can be seen in item A13 in the Appendix. Additionally, we also received 3 demographic variables which were collected automatically when the respondent logged in to answer the survey.

Possible weaknesses of the dataset

In the 2011 FHI report on the condition of mental health in Norway, they bring attention to the possible sampling error in their study. People struggling with mental health might be averse or hesitant to participate in mental health related studies (FHI, 2011). This is an example of systematic non-response error, which can lead to biased estimates.

Table 7: Distribution of respondents divided for age groups and gender.

Age groups	Gender		Total
	Female	Male	
18-24	919	460	1 379
25-44	4 936	3 396	8 332
45-64	6 119	5 135	11 254
65-74	1 868	2 052	3 920
75+	459	695	1 154
Total	14 301	11 738	26 039

Looking at table 7, we fear that there might be systematic differences between the non-responses for the different genders. Men exposed to mental health problems might have been *more* averse or hesitant to participate in the study, which would mean that the estimate for the "female" variable in our model might be biased. This might be especially prevalent for the youngest age group as table 7 showed that only a total of 460 men, compared to 919 women, in the 18-24 age group responded to the survey. There might also be systematic differences in the non-response for the oldest age group compared to the other age groups. SSB has stated that, in web-based surveys, the oldest age group mainly represents the elders who are healthy, who are digitally capable and who have a good network around them to ask for help (SSB, 2020). This could lead to systematic non-response error, and therefore biased estimate for the "age75+" variable.

A combination of systematic non-response and low response rates can cause severely biased estimates (Jones, 1996). As we just covered, there might be reason to believe that there are systematic non-response errors. However, we are not able to conclude that there is also bias due to lower response rates in the different groups. This is due to us not having the necessary information to tell if there are low response rates for the different groups.

We had missing observations on both the y-variable and several of the x-variables. As these respondents were removed from the dataset, our final dataset suffers from yet another potential problem. If there is a systematic reason for the respondents not answering, e.g., by exposed respondents refraining from answering as they do not want to admit that they are, this would mean that we have sample bias. This might have been the case for a question about their economy, where there was a total of 2 449 missing answers. It might be that people do not want to admit that they find their economy to be challenging, and therefore not answer because of this. This would, in other words, mean that the final sample would not be representative for the population in question. In the end, the dataset we used had 17 880 respondents after removing the respondents with missing observations.

5.2 Dependent variable

The dependent variable in our model is "mentalill". This is a generated dummy variable which takes on the value of 1 if the respondent had an HSCL-5 average score above 2. This is defined as the threshold value for having considerable mental health problems.
Their score depends on the answers they gave to the HSCL-5 questionnaire. The respondent did not receive a score if they refrained from answering one of these questions, which was the case for 306 of the respondents. These respondents were subsequently removed from the dataset. 15.8% of the respondents in our model are defined as having considerable mental health problems, see table 8.

Table 8: Descriptive statistics for "Mentalill"

Considerable mental problems	Share
Respondent has a HSCL-score of >2	15,8 %
Respondent has a HSCL-score of <2	84,2 %
Total	100 %

5.3 Explanatory variables

The explanatory variables we have used in our model are mainly dummy variables. We have created dummy variables for different age groups, gender, singlehood, higher education, unemployment, and self-perceived economic situation. In this section of the chapter, we provide descriptive statistics for the explanatory variables in our model and explain changes we have made to them.

The only variables in the dataset that had no missing observations were the age groups and gender. This is due to the requirement of having to log in to Helse Norge with personal credentials to be able to answer the survey. The rest of the variables, however, all suffer from missing observations to some degree. Some of the questions in the survey may be considered sensitive for some people, and they might therefore completely refrain from answering the question. We removed the missing observations from the dataset, but this might have severely weakened our analysis - which we talked about in section 5.1.

Age groups

The respondents in our dataset are aged 18 and above. They are grouped as 18-24, 25-44, 45-64, 65-74 and 75+. 45-65 is the biggest age group in our data, with 32% of all respondents belonging to this group. Due to the fact that this group is the largest, it is suitable to use it as the reference group to compare the other groups with. By doing this, we avoid falling into the dummy variable trap. We created dummy variables for each of the other age groups, and these are included in our model.

Table 9: Descriptive statistic for the age groups.

Age group	Share
18-24	5,3 %
25-44	32,0 %
45-64	43,2 %
65-74	15,1 %
75+	4,4 %
Total	100 %

Female

"Female" is an explanatory variable which holds the value of 1 if the respondent is a woman and 0 if the respondent is a man. Table 10 below shows there are more women than men in the survey, with women accounting for almost 55% of the responses.

Table 10: Descriptive statistic for gender.

Gender	Share
Female	54,9 %
Male	45,1 %
Total	100 %

Higheredu

The "higheredu" variable measures the level of education that the respondents have. In the raw dataset, the type of education the respondent held was categorized into four groups. Those with only a primary school or folk high school education, those with high school or vocational education, those with a college education up to four years, and those with a college education above four years. As we were interested in seeing the effect on those with a lower level of education compared to those with higher, we decided to merge the groups. We generated a new variable, called “higheredu” which contains the respondents that hold a college degree. We no longer separate those with up to four years of college educations and those with more than four years. Our reference group is the respondents with a lower degree of education. The “higheredu” variable takes on the value of 1 if the respondent has a college education and takes on the value of 0 if they do not. Approximately 59% of the respondents holds a college degree, and therefore takes on the value of 1 on the “higheredu” variable.

Table 11: Descriptive statistic for education.

Education	Share
Primary or Folk high school	9,6 %
High school or vocational education	31,4 %
College education up to four years	26,9 %
College education more than four years	32,1 %
Total	100 %

Oslobergen

The explanatory variable “oslobergen” is a variable that we have generated based on the question regarding the location of the respondents. The dataset split the respondents into five locations: Oslo, Bergen, Agder, Nordland and Vestland w/o Bergen. We have merged the respondents that were in Oslo and Bergen and treated them as one group. In other words, the dummy variable “oslobergen” equals to 1 if the respondent lives in one of these cities and equals to 0 if the respondent lives in Agder, Nordland or Vestland w/o Bergen. We use the variable as a way of controlling for stricter COVID-19 measures, since both Bergen and Oslo had stricter measures than the other locations in the dataset (FHI, Nov/Dec 2020).

Table 12: Descriptive statistic for place of home.

Place of home	Share
Oslo or Bergen	45,9 %
Agder or Nordland or Vestland without Bergen	54,1 %
Total	100 %

Single

The variable “single” is a dummy variable which takes on the value of 1 if the respondent reported that they were single, which was the case for 22.6%. The respondent takes on the value of 0 if they reported to be either married, have a domestic partner, or have a boy- or girlfriend.

Table 13: Descriptive statistic for singlehood.

Marital status	Share
Married or have a registered partner	49,0 %
Domestic partner	21,6 %
Boyfriend or girlfriend	6,8 %
Single	22,6 %
Total	100 %

Childund18

Alon et al point out increased childcare as one of the explanations for the differences in mental health problems between men and women (Alon et al, 2020). We wanted to somewhat control for this effect by including “childund18” as a variable in our model. The survey does not account for whether children reported actually live in the house. The respondent may have children from a previous relationship who do not live in the same household as the respondent. They may, however, still consider these children to be under their care although they live with the other parent.

Table 14: Descriptive statistic for number of children under the age of 18 in respondents’ care

Number of children under the age of 18 in respondent's care	Share
0	69,4 %
1	12,3 %
2	13,3 %
3	4,4 %
4	0,5 %
5	0,1 %
Total	100 %

Challeco

Another explanatory variable we used in our model was “challeco”. This is a variable we generated based on a question in the survey regarding how difficult the respondent finds it to make ends meet, given their income. Those that answered that they found it to be either relatively difficult, difficult, or very difficult to make ends meet, took on the value of 1 for the “challeco” variable. 16.6% of the respondents fell into this group.

Table 15: Descriptive statistic for reported economic challenges.

Given your income, how difficult is it to make ends meet?	Share
Very difficult	2,4 %
Difficult	3,8 %
Relatively difficult	10,4 %
Relatively easy	26,4 %
Easy	26,5 %
Very easy	28,9 %
Do not know	1,6 %
Total	100 %

Table 16: Descriptive statistic for “challeco”.

Challeco	Share
The respondend reported having economic challenges	16,6 %
The respondent did not report having economic challenges	83,4 %
Total	100 %

Withoutwork

We also wanted to see what role the respondent’s work status has on the probability of having considerable mental health problems. The “withoutwork” variable was one of the more challenging variables we generated due to the fact that the respondent could pick multiple options in the survey. Being able to pick multiple answer options allows for misinterpretation of the question.

E.g., the respondent was able to report that they were both unemployed and a part-time employee. While it can make sense that they were partly unemployed, and therefore answered both, this meant that we could not simply take the “unemployed” variable in the original dataset at face value. From the respondent’s point of view, this answer could also have meant that they are normally a part time employee but are unemployed at the current time. Being able to pick multiple answer options allows for misinterpretation of the question. We also found that multiple people had answered that they were both unemployed and put on furlough, although they are mutually exclusive. There was also an alternative with the Norwegian name “hjemmearbeidende” which for some may be an unknown term for being a stay-at-home parent or home maker. The respondent might have misinterpreted it as “working from home” instead.

We created the dummy variable “Withoutwork” which would take on the value of 1 if the respondent either was unemployed or on disability benefits without having a part- or full-time job, being self-employed, studying, being conscripted, or receiving pension. We did this as an effort to separate those who are completely out of work with the rest. In other words, those who took on the value of 1 for the “Withoutwork” variable in our model only reported being unemployed or on disability benefits, without checking for any of the other options.

Table 17: Descriptive statistics for work status.

Work status	Share
Working full-time (32h/week)	49,7 %
Working part-time (<32h/week)	9,2 %
The respondent is self-employed	4,5 %
The respondent is on furlough	1,7 %
The respondent is on sick leave	2,7 %
The respondent is unemployed	2,0 %
The respondent is on disability benefit	8 %
The respondent receives social assistance	0,3 %
The respondent is on pension	15,7 %
The respondent is a student	5,5 %
The respondent is conscripted in the military	0,1 %
The respondent is a full-time parent	1,0 %
Total	100 %

Table 18: Descriptive statistics for “Withoutwork”.

Withoutwork	Share
The respondent is fully without work	8,4 %
The respondent is not fully without work	91,6 %
Total	100 %

We also wanted to see the effect of becoming unemployed due to COVID-19, and the dataset we received from FHI included a question about this. The question was worded like this: “Have your work situation changed as a result of the pandemic?”. The response options were the following: “Yes”, “No” or “Is not working”. You were only able to respond with one of these three options. This, combined with the wording of the response options seem to have created some confusion for the respondents. Ultimately this rendered the question and the respective answers useless in our eyes, and we decided to not include it in our analysis.

5.4 Interaction variables

In addition to the explanatory variables that we included in our model, we also created three interactions in order to see how some of the explanatory variables in our model interact with each other. Our Benchmark model showed that the younger age groups, females, and those reporting having a challenging economy were especially exposed to having considerable mental health problems. See table A14 in the Appendix. Based on this, we created interactions between “age18_24” and “female”, “challeco” and “female”, and “age18_24” and “challeco”. However, we only added one interaction by itself to the Benchmark model, and thus created Model 2, 3 and 4 to avoid multiplicity and multicollinearity.

6 Results

In the following chapter we will go through the results our models gave us. We present Model 3's logistic regression results in the form of OR's and margins and interpret the marginal effects for the explanatory variables in our model, to try to answer the research question. We will then look at a small extract from Model 2 and 3 to interpret the interaction terms they incorporated. In the end, we compare some of our OR's with relevant OR's from the FHI 2011 report.

6.1 Interpretation of Model 3

The first column in table 22 includes the name of all the x-variables in Model 3. The second column includes the x-variables' OR's, and third and fourth columns show the x-variables' heteroskedastic robust standard errors and the corresponding p-values. The fifth, sixth and seventh column consists of the x-variables' marginal effects, their corresponding delta method standard errors and their p-values, respectively.

Table 19: OR's and marginal effects for Model 3.

Model 3						
Coefficients	Odds ratio	Standard error	P >|z|	Marginal effect	Standard error	P >|z|
Intercept	0.0614	0.0046	0.000***	-	-	-
oslobergen	1.5624	0.0734	0.000***	0.0501	0.0052	0.000***
female	1.9123	0.1063	0.000***	0.0728	0.0062	0.000***
higheredu	0.9261	0.0459	0.122	-0.0086	0.0056	0.122
single	1.4004	0.0915	0.000***	0.0378	0.0073	0.000***
age18_24	3.9940	0.3353	0.000***	0.1555	0.0092	0.000***
age25_44	2.5259	0.1397	0.000***	0.1040	0.0061	0.000***
age65_74	0.5525	0.0558	0.000***	-0.0666	0.0113	0.000***
age75over	0.7016	0.1213	0.040*	-0.0398	0.0194	0.040*
childund18	0.8474	0.0223	0.000***	-0.0186	0.0029	0.000***
challeco	4.1751	0.3552	0.000***	0.1605	0.0094	0.000***
withoutwork	2.2293	0.1612	0.000***	0.0900	0.0081	0.000***
female_challeco	0.5568	0.0592	0.000***	-0.0657	0.0119	0.000***
* $p<0.05$, ** $p<0.01$, *** $p<0.001$						
N = 17 880						
Pseudo $R^2 = 0.1328$						
Nagelkerke $R^2 = 0.187$						
Cox & Snell $R^2 = 0.107$						

Like previously stated, every variable except “childund18” is a dummy variable. However, “childund18” is not included in our research question and is therefore only used as a control variable. For dummy variables we interpret the coefficients by comparing them to their corresponding reference variables. Since “childund18” is a discrete variable, the interpretation is different, as we look at what effect a one unit increase in childund18 has on the y-variable. Model 3 also included the “female_challeco” interaction.

Coefficient β_1 corresponds to the “oslobergen” variable. The estimated coefficient is statistically significant at the $p < 0.001$ level. By looking at the marginal effect, we can see that living in Oslo or Bergen is associated with a 5.01% increased probability of having considerable mental health problems, compared to living in Agder, Nordland and Vestland w/o Bergen, controlled for all the other variables in the model. In other words, those living in Oslo or Bergen are associated with a 5.01% increased probability of the y-variable “mentalill” being equal to 1. We do not emphasize this effect, due to it not being a part of our research question. FHI reported that these two cities had stricter measures than the other locations in the dataset (FHI, Nov/Dec 2020). We wanted to control for stricter measures when looking at the effects of the different explanatory variables in the research question. The variable was therefore only included in the model as a control variable. There is also uncertainty about general differences in mental health between living in large cities such as Bergen and Oslo, compared to smaller cities and more rural areas. We were not able to find any data on there being any differences in terms of mental health problems between the aforementioned locations, but the “oslobergen” variable might also inadvertently control for this if there in fact is a difference.

Coefficient β_2 corresponds to the “female” variable and is statistically significant at the $p < 0.001$ level. Being female compared to being male is associated with a 7.28% increase in probability of having considerable mental health problems. This is consistent with the FHI 2011 and HCEO 2020 studies. The studies during economic recessions we covered in chapter 2, however, had mixed results. E.g., studies from England and Spain showed that the increase of mental distress during the recession had a greater impact on men than women (Katikireddi et al., 2012, Bartoll et al., 2014). This is in direct contrast to our findings. Alon et al (2020) reported that increased childcare could be a possible explanation for the mental health gender gap.

By adding “childund18” as a control variable, we may be able to control for some of this effect. The “female” variable is also used in the interaction with “challeco” in the model, and it is therefore important to note that the previously mentioned effect of 7.28% is only for females that do not report that their economy is challenging (“challeco” = 0).

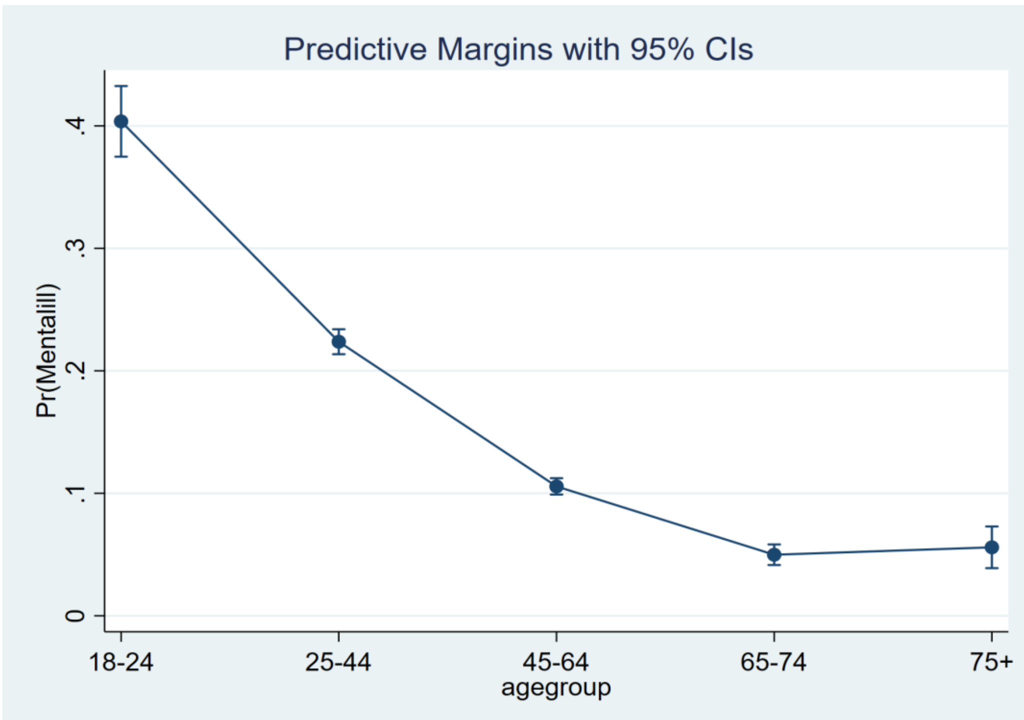
The β_3 coefficient corresponds to the “higheredu” variable. Having a higher education compared to having lower education is associated with a 0.86% decrease in the probability of having considerable mental health problems. However, this relation was not statistically significant at the $p < 0.05$ level.

The variable “single” is corresponding to the β_4 coefficient. Being single, compared to being in some form of relationship, is associated with a 3.78% increase in the probability of having considerable mental health problems. The variable was statistically significant at the $p < 0.001$ level. This finding is consistent with the SSB 2020, FHI 2019 and HCEO 2020 studies. This might be related to the lack of social support that comes with being in a form of relationship (Fyrand, 1994).

The β_5, β_6, β_7 and β_8 coefficients correspond to the age groups. The reference group is the respondents that are between 45 and 64 years old. Being in the 18-24 age group is associated with an 15.55% increased probability of having considerable mental health problems, compared to the reference group. Being in the 25-44 years group is associated with an increased probability of 10.40%. However, for the two oldest age groups, the probability is reduced compared to the reference group. For the respondents between 65 and 74 years, the probability is 6.66% lower, while those above 75 were associated with a decreased probability of 3.98%. All the coefficients for the age groups are significant at the $p < 0.001$ level, except for the oldest age group which was significant at the $p < 0.05$ level. To summarize, the probability is the highest for the youngest age group. The probability is decreasing by age until it increases somewhat from the 65-74 age group to the 75+ age group. This relation between the y-variable and the age groups is showcased in figure 4. As the figure shows, 40% of the respondents in the age group 18-24 scored over the threshold value for considerable mental health problems.

It might be that the estimate for 75+ is biased, as we have pointed to the fact that mainly the healthiest of the elders are normally able to answer web-based health surveys. Therefore, the estimate might in reality be higher. This has been a recurring problem in these types of research according to FHI and SSB (FHI 2020; SSB 2020).

Figure 4: Plot of the relation between "mentalill" and the age groups.



The only discrete variable in our model "childund18" corresponds to coefficient β_9. Going from having 0 to 1 child under the age of 18 in the respondent's care is associated with a 1.86% decreased probability of having considerable mental health problems. The coefficient is statistically significant at the $p < 0.001$ level. This relation is in contrast to the findings made by Alon et al, who reported that the mental health gender gap was due to increased childcare coming at the expense of leisure (Alon et al, 2020).

The next coefficient is β_{10} and corresponds to the "challeco" variable. Those who reported that they were having economic challenges were associated with a 16.05% higher probability of having considerable mental health problems compared to those who reported not having economic challenges. Because of the interaction "female_challeco", this effect is only applicable to men ("female" = 0). This relation was found to be significant at the $p < 0.001$ level and is consistent with the findings from FHI 2011.

The β_{11} coefficient corresponds to the "withoutwork" variable. Those who are, after our impression, fully out of work are associated with a 9% higher probability of having considerable mental health problems compared to those who are not fully out of work. This relation is significant at the $p < 0.001$ level. The finding is consistent with FHI 2011 report's findings, and the SSB 2020 life quality report. The SSB 2020 report found that those who were unemployed reported to be less satisfied with their own mental health.

Lastly, we have the interaction variable "female_challeco" which corresponds the coefficient β_{12} that separates Model 3 from the Benchmark model and Model 2 and 4. The interaction term shows us that the associated increase in probability of having considerable mental health problems by being a female, compared to being male, is 0.71% when the female respondent also considers her economy challenging (0.0728 + (-0.0657) = 0.0071). The interaction term also tells us that the probability of having considerable mental health problems is increased by 9.48% (0.1605 + (-0.0657) = 0.0948) for the respondents that consider their economy challenging, compared to those who do not find their economy challenging, and are female. In other words, the effect of "challeco" is smaller for women than for men, as the effect was 16.05% for men. The interaction term is significant at the $p < 0.001$ level. Although the effect of having a challenging economy seems to be higher for men, the percentage of women who report economic challenges are higher, see table 20. This might be skewed, if in fact more men that are exposed to economic challenges avoid responding to the question about "challeco" or the survey as a whole.

Table 20: HSCL-5 > 2 percentages for men and women with reported having economic challenges.

HSCL-5 > 2 - percentage after gender and challeco			
	Men	Women	Total
Challeco = 1	30.7	37.3	34.5

Table 21: Small extract from Model 2.

Model 2						
Coefficients	Odds ratio	Standard error	P >|z|	Marginal effect	Standard error	P >|z|
female_age18_24	1.4044	0.2203	0.030*	0.0381	0.0176	0.030*
female	1.5081	0.0780	0.000***	0.0513	0.0055	0.000***
age18_24	3.1167	0.4351	0.000***	0.127	0.0156	0.000***
* p<0.05, ** p<0.01, *** p<0.001						
N = 17 880						
Pseudo R^2 = 0.1311						
Nagelkerke R^2 = 0.184						
Cox & Snell R^2 = 0.106						

Table 21 shows a small extract from Model 2's output. For the complete output, see tables A15 and A16 in the Appendix. The table shows that the probability of having considerable mental health problems if the respondent is a woman and not in the 18-24 age group is 5.13% higher compared to men who are not in the 18-24 age group. The interaction shows us that the probability is 8.94% (0.0513 + 0.0381 = 0.0894) higher for being a woman compared to being a man, when the respondent is in fact between the age of 18 and 24. According to Model 2, being between the age of 18 and 24, compared to the reference group, is associated with a 12.7% higher probability when the respondent is male. The effect is instead 16.51% (0.127 + 0.0381 = 0.1651) being between the age of 18 and 24 compared to the reference group, when the respondent is female.

The "female" and "age18_24" variables are significant at the $p < 0.001$ level, while the interaction is significant at the $p < 0.05$ level. These results indicate that women are the most exposed in the 18-24 age group, which is also the most exposed age group. This seems consistent with table 22.

Table 22: HSCL-5 > 2 percentages for men and women between the ages of 18 and 24.

HSCL-5 > 2 - percentage after gender and age group 18-24			
	Men	Women	Total
Age 18-24	29.4	45.4	40

Table 23: Small extract from Model 4.

Model 4						
Coefficients	Odds ratio	Standard error	P >|z|	Marginal effect	Standard error	P >|z|
age18_24_challeco	0.7875	0.1243	0.130	-0.0268	0.0177	0.130
age18_24	4.2425	0.4022	0.000***	0.1623	0.0105	0.000***
challeco	3.0065	0.1770	0.000***	0.1236	0.0065	0.000***
* p<0.05, ** p<0.01, *** p<0.001						
N = 17 880						
Pseudo R^2 = 0.1310						
Nagelkerke R^2 = 0.184						
Cox & Snell R^2 = 0.106						

For the complete output of Model 4, see table A17 and A18 in the Appendix. Model 4 found that having economic challenges is associated with an increased probability of 12.36% for having considerable mental health problems if the respondent is not aged between 18 and 24. This is significant at the $p < 0.001$ level. When the respondent is between the ages of 18 and 24, the effect of having economic challenges becomes 9.68% (0.1236 + (-0.0268) = 0.0968). However, the interaction is not statistically significant at the $p < 0.05$ level.

The model finds that, when compared to the reference group, being between the age of 18 and 24 is associated with a 16.23% increased probability of having considerable mental health problems given that the respondent does not consider their economy challenging. For the respondents that do consider their economy challenging and are between the ages of 18 and 24 the probability increased with 13.55% (0.1623 + (-0.0268) = 0.1355), but again - the interaction is not statistically significant. If the interaction was significant, it would have indicated that the effect of having a challenging economy is lower for the ones that are in the youngest age group. Furthermore, this would have indicated that a challenging economy is not the reason for this age group to be the most exposed age group in our results.

Table 24 shows that 55.8% of the respondents between the age of 18 and 24 had considerable mental health problems if they also reported economic challenges. For those who did not report economic challenges, the percentage was 35%. As the interaction above is not statistically significant we cannot conclude what percentage of increased considerable mental health problems the ones in the age group 18-24 with economic challenges is associated with, but it seems likely that it is a considerable amount.

Table 24: HSCL-5 > 2 percentages for age 18-24 with and without reported having economic challenges.

HSCL-5 > 2 - percentage after age group 18-24 and challeco			
	Challeco = 1	Challeco = 0	Total
Age 18-24	55.8	35	41

6.2 Comparing our results with the FHI 2011 report.

Table 25: Comparison of OR's for economic problems and being without work with the FHI 2011 report.

	Our OR's for having HSCL-5 > 2	FHI 2011 OR's for having HSCL-25 > 1,75
Economic problems	4,18	10,48
Being without work	2,23	3,55

Table 25 shows the OR's we found for economic problems ("challeco") and unemployment ("withoutwork") in comparison with FHI 2011's findings for similar variables. However, there are several issues with comparing these OR's. First of all, the variables we used and those of the FHI 2011 report may be somewhat different. While we regarded all respondents who reported facing fairly, hard, or very hard economic challenges as one group, FHI 2011 characterized their economic challenges group as those having "severe" economic problems. Because of this, their group might only consist of those who faced very hard economic challenges. There might also be differences as to what we consider to be the "without work" compared to the FHI 2011 report. Their group consisted of only those who had been unemployed for the last three months. Whereas our respondents were asked to provide their work situation at the time they answered the survey. The reason we wanted to compare these OR's is that we would like to see if there are differences between the effects during the COVID-19 pandemic compared to a situation without COVID-19. As social context might be an important factor, we wanted to compare with another Norwegian study, but unfortunately the last study that had similar explanatory factors was the FHI 2011 report.

Our dependent variable was linked to the HSCL-5 questions, while the FHI 2011 report used HSCL-25 score as dependent variable. Because of this, the threshold score needed in order to be classified as having considerable mental health problems differed between our models. Therefore, receiving Y = 1 in our models is not based on the exact same criterion. Our OR's are controlled for several other explanatory variables, while the FHI 2011 report only controls for age and gender. As we discussed in the endogeneity part of chapter 4, our model might suffer from OVB. This would perhaps be even more prevalent for the FHI 2011 report, as they included fewer control variables. Table 25 seems to indicate that the two variables are associated with a higher OR for the FHI 2011 report, with OR's of 10.48 and 3.55 for the economic problems and being out of work variables compared to 4.18 and 2.23 in our findings, respectively. Does this mean that the effect of these variables had a larger effect in a time without COVID-19? Because of the problems just mentioned, it is not possible to reach such a conclusion.

Looking at table 26, we see that out of the respondents in the age group 18-24, 29.4% of men and 45.4% of women in this group had considerable mental health problems.
In comparison, the FHI 2011 report found that 6.8% of men and 24% of women had considerable mental health problems. However, the age group that FHI used spanned between 16 to 24. In total, 16.5% of the respondents in their age group scored above the threshold score, while 40% of our respondents had the same result. These findings could indicate that the youngest age group is more affected in terms of considerable mental health problems during COVID-19, compared to in 2011 when COVID-19 did not exist.

Table 26: Comparison of percentages for men and women in the youngest age group.

FHI Nov/Des 2020 (Our dataset)			
HSCL-5 > 2 - percentage after gender and age group 18-24			
	Men	Women	Total
Age 18-24	29.4	45.4	40

FHI 2011			
HSCL-25 > 1.75 - percentage after gender and age group 16-24			
	Men	Women	Total
Age 16-24	6.8	24.0	16.5

6.3 Interpreting R2s

In logistic regression we cannot use the standard R^2 from OLS. This measure is able to show the model's explained variance by seeing how much of the variance in Y that can be explained by X (Warner, 2013). This would be a measurement of the model's strength. In logistic regression a range of different R^2s are used, but they are not equipped to be a measurement of the strength of the model. Instead, they are used to compare different models on the same data. However, adding another variable to the model would make the R^2s in logistic regression higher, no matter if the variable added is a good fit for the model or not. This is a part of the reason why the $R^{2'}$s used in logistic regression are not able to measure the strength of the model (Tufte, 2000).

Stata uses the McFadden's' Pseudo R^2 by default for logistic regression, but we also included the Nagelkerke and Cox & Snell R^2s to compare our different models. Model 3 was the best model according to these 3 measures, but it is important to note that the Benchmark model is at a disadvantage because of the aforementioned problem with the $R^{2'}$s being biased towards having more variables in the model, no matter their relevance. The $R^{2'}$s are showcased in table 27. Model 3 ended up being our final model as it also had the best fit according to the Hosmer-Lemeshow test, best percentage of correctly classified observations according to the *estat classification* command in Stata, and the least amount of multicollinearity out of the three models with an interaction.

Table 27: McFadden's Pseudo R^2, Nagelkerke R^2 and Cox & Snell R^2 for our models.

	Benchmark model	Model 2	Model 3	Model 4
McFadden's Pseudo R^2	0.1308	0.1311	0.1328	0.1310
Nagelkerke R^2	0.184	0.184	0.187	0.184
Cox & Snell R^2	0.106	0.106	0.107	0.106

7 Discussion and conclusion

In this thesis we have used a multiple logistic regression model on a dataset from November and December 2020 to research the role of gender, age, education, economic situation, unemployment, and singlehood on the probability of having considerable mental health problems during the COVID-19 pandemic. The dataset limits us to a population of Oslo, Agder, Nordland and Vestland. We ended up using Model 3 to answer the research question. Model 3 used “oslobergen” as a control variable for stricter measures and “childund18” as a control variable for childcare. It also included an interaction variable between being female and having economic problems.

When it comes to gender, we found that, during the COVID-19 pandemic, women were found to be associated with a 7.28% higher probability of having considerable mental health problems, compared to men, if the respondent did not report having economic challenges. In contrast, we found that the associated probability for having considerable mental health problems is 0.71% higher for women compared to men, when the women report having a challenging economy.

For education, we found having a higher education compared to having lower education was associated with a 0.86% decrease in the probability of having considerable mental health problems. However, this relation was not statistically significant at the $p < 0.05$ level. Due to the explanatory variable not being statistically significant, we are unable to say what role having an education plays on the probability of having considerable mental health problems during the COVID-19 pandemic.

For being single, we found that being single during the COVID-19 pandemic was associated with a 3.78% increase in the probability of having considerable mental health problems.

For age, we found that during the COVID-19 pandemic, those in the youngest age group had the highest prevalence of considerable mental health problems during the COVID-19 pandemic, with approximately 40% of the age group scoring above 2 on the HSCL-5. The youngest age group also had the highest probability of having considerable mental health problems during the pandemic. Compared to the reference group, age 45-64, the youngest age group is associated with a

15.55% higher probability of having considerable mental health problems. This probability decreases with higher age. However, the relation turns between the age groups 45-64 and 75+, where the probability somewhat increases again.

For economic situations, we found that those who reported that they were having economic challenges were associated with a 16.05% higher probability of having considerable mental health problems compared to those who reported not having economic challenges, given that the respondent was a man. If the respondent is a woman, and reported having economic challenges, we found that they were associated with a 9.48% higher probability of considerable mental health problems, compared to the women who did not report economic challenges.

For unemployment, we found that the correspondents that were fully out of work at the time of the survey were associated with a 9% higher probability of having considerable mental health problems, compared to those who were not fully out of work.

To summarize the research question; gender, age, economic situation, unemployment, and singlehood all play a role on the probability of having considerable mental health problems during the COVID-19 pandemic. Being a woman, being in the younger age groups, having economic challenges, being unemployed and being single are all associated with a higher probability of having considerable mental health problems during the pandemic.

However, we need to be cautious when looking at our findings. The internal validity of our model is heavily weakened by the endogeneity issue, discussed in chapter 4. The estimates produced by our models might be inconsistent and biased. Our model suffers from endogeneity both because of OVB and simultaneity bias. We still believe our findings hold some value, as they are for the most part consistent with previous research - especially in the Norwegian social context.

We had a considerable number of missing observations on the x-variables, and the respondents with missing observations were subsequently removed from the sample. If there was a systematic reason for these respondents not answering, this would mean that the final sample is not representative for the population in question. The missing observations might be systematic, if e.g., some of the respondents do not answer the question about their personal economy because they do not want to admit it being difficult.

Non-response error might also have led to biased estimates in our analysis. People exposed to mental health problems might be averse or hesitant to participate in mental health related surveys (FHI, 2011). This might have been the case for the survey we base our dataset on. It might especially be prevalent for the estimates for the oldest age group variable. SSB have stated that, in web-based surveys, the oldest age group mainly represents the elders who are healthy, who are digitally capable and who have a good network around them to ask for help (SSB, 2020).
We also fear that there might be systematic differences between the genders, especially for the youngest age group. It might be that men exposed to mental health problems are more averse or hesitant to participate in the study, and therefore the "female" variable could be biased.

The total response rate for the study we based our dataset on was 44.9%. We do not know the response rates for the different age groups or genders. Our variables might also be biased because of systematic low response rate for certain groups, e.g., for men in the youngest age group. Table 7 showed that only a total of 460 men, compared to 919 women, in the 18-24 age group responded to the survey.

Another weakness with our study is that we are unable to say anything about the changes in effect during the COVID-19 pandemic compared to pre-COVID-19. The main reason for this is that there have not been any surveys done on mental health as a main subject in Norway since the FHI report in 2011. Although the 2011 report focused on mental health, there were many differences between the models, with the main differences being different questionnaires and using different explanatory factors. Thus, we have only been able to study what roles the different explanatory factors have played during the pandemic, without being able to see change in the explanatory factors from before the pandemic.

Knowing what role the explanatory factors play on the probability of having considerable mental health problems may also be valuable for policy decisions if we were to find ourselves in a similar situation in the future. By seeing the prevalence of mental health problems in the different groups during the pandemic, policy makers should try to ensure that these exposed groups receive proper consideration before decisions are made. We emphasize the importance of doing more research into the effect of the pandemic on mental health, and especially on the possible long-term effects. We also hope for more research into the different explanatory factors, as we need to understand especially how the factors affect each other to be able to take endogeneity into account and make better models in the future.

Ultimately, we hope that this thesis can inspire future research on what we believe to be an immensely important subject. The economic cost of these problems is extensive, and more importantly - the human cost is unaffordable.

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The Appendix

A1: The Pearson and the Hosmer Lemeshow goodness of fit test for the Benchmark model.

```
. estat gof

Logistic model for mentalill, goodness-of-fit test

       number of observations =     17880
 number of covariate patterns =       641
             Pearson chi2(629) =      788.32
                  Prob > chi2 =        0.0000

. estat gof, group(10)

Logistic model for mentalill, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =     17880
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =       17.37
                  Prob > chi2 =        0.0265
```

A2: The Pearson and the Hosmer Lemeshow goodness of fit test for Model 2.

```
. estat gof

Logistic model for mentalill, goodness-of-fit test

       number of observations =     17880
 number of covariate patterns =       641
             Pearson chi2(628) =      780.07
                  Prob > chi2 =        0.0000

. estat gof, group(10)

Logistic model for mentalill, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =     17880
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =       17.50
                  Prob > chi2 =        0.0253
```

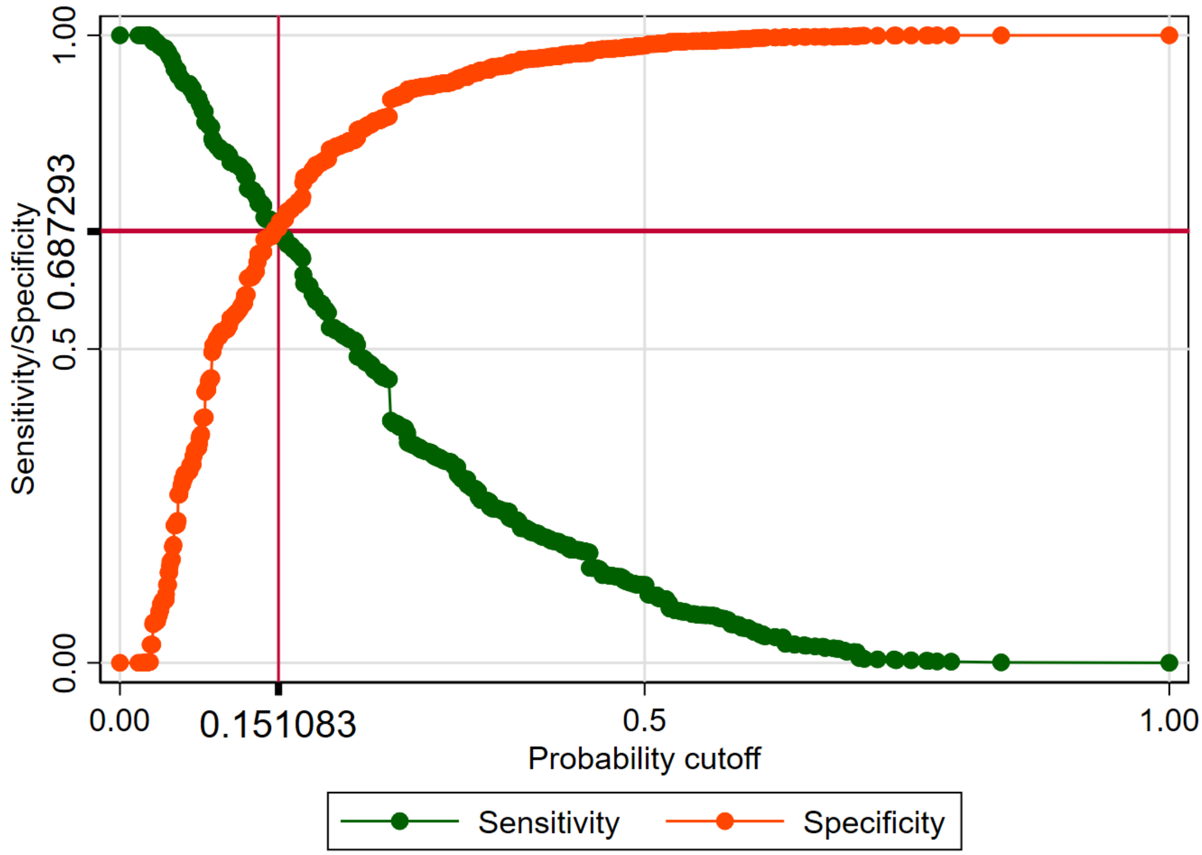
A3: The Pearson and the Hosmer Lemeshow goodness of fit test for Model 3.

```
. estat gof

Logistic model for mentalill, goodness-of-fit test

       number of observations =     17880
 number of covariate patterns =       641
             Pearson chi2(628) =    753.88
                   Prob > chi2 =    0.0004

. estat gof, group(10)

Logistic model for mentalill, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =     17880
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =     13.52
                   Prob > chi2 =    0.0952
```

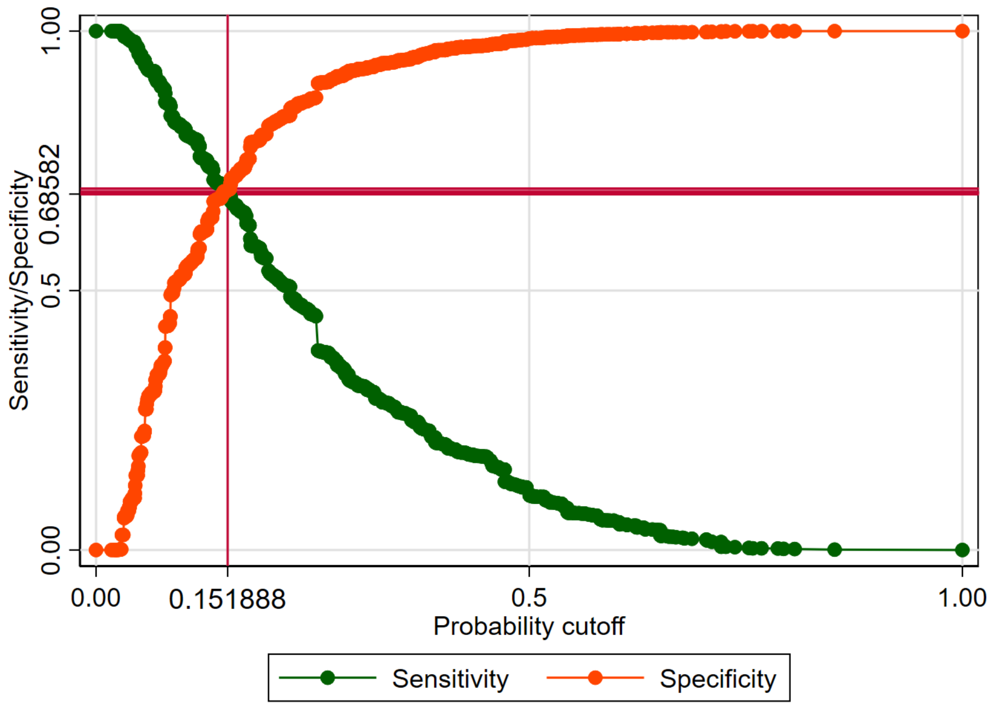
A4: The Pearson and the Hosmer Lemeshow goodness of fit test for Model 4.

```
. estat gof

Logistic model for mentalill, goodness-of-fit test

       number of observations =     17880
 number of covariate patterns =       641
             Pearson chi2(628) =    785.59
                   Prob > chi2 =    0.0000

. estat gof, group(10)

Logistic model for mentalill, goodness-of-fit test

  (Table collapsed on quantiles of estimated probabilities)

       number of observations =     17880
             number of groups =        10
      Hosmer-Lemeshow chi2(8) =     19.29
                   Prob > chi2 =    0.0134
```

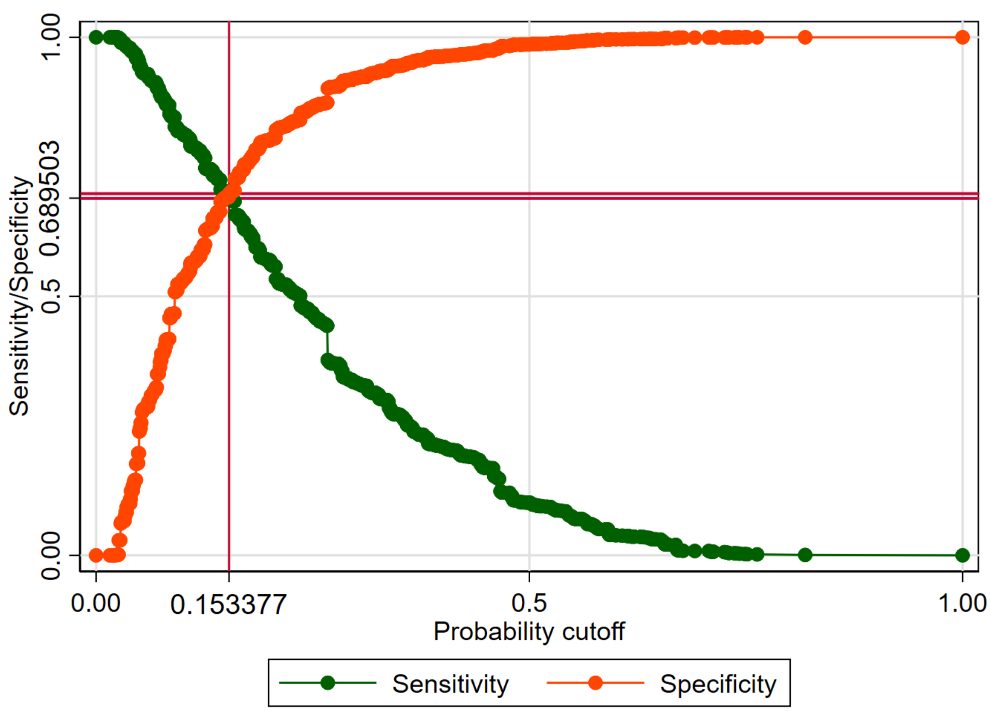
A5 - Result of *lsens* for Benchmark model, finding relevant probability cut-off for *estat classification*



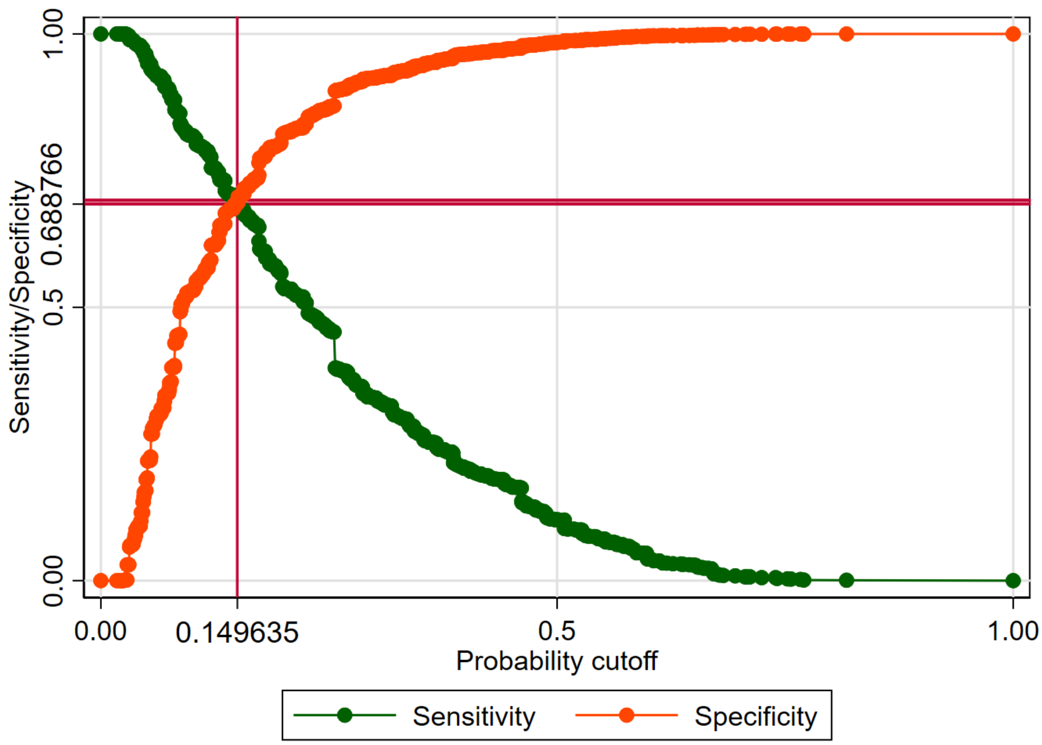
A6 - Result of *lsens* for Model 2, finding relevant probability cut-off for *estat classification*



A7 - Result of *lsens* for Model 3, finding relevant probability cut-off for *estat classification*



A8 - Result of *lsens* for Model 4, finding relevant probability cut-off for *estat classification*



A9 - *Estat classification* results for the Benchmark model, with relevant probability cut-off

Logistic model for mentalill

Classified	True D	True ~D	Total
+	**1866**	**4661**	**6527**
-	**849**	**10504**	**11353**
Total	**2715**	**15165**	**17880**

Classified + if predicted Pr(D) >= .1510826
True D defined as mentalill != 0

Sensitivity	Pr(+| D)	**68.73%**
Specificity	Pr(-|~D)	**69.26%**
Positive predictive value	Pr(D| +)	**28.59%**
Negative predictive value	Pr(~D| -)	**92.52%**
False + rate for true ~D	Pr(+|~D)	**30.74%**
False - rate for true D	Pr(-| D)	**31.27%**
False + rate for classified +	Pr(~D| +)	**71.41%**
False - rate for classified -	Pr(D| -)	**7.48%**
Correctly classified		**69.18%**

A10 - *Estat classification* results for Model 2, with relevant probability cut-off

Logistic model for mentalill

Classified	True D	True ~D	Total
+	**1861**	**4632**	**6493**
-	**854**	**10533**	**11387**
Total	**2715**	**15165**	**17880**

Classified + if predicted Pr(D) >= .1518879
True D defined as mentalill != 0

Sensitivity	Pr(+| D)	**68.55%**
Specificity	Pr(-|~D)	**69.46%**
Positive predictive value	Pr(D| +)	**28.66%**
Negative predictive value	Pr(~D| -)	**92.50%**
False + rate for true ~D	Pr(+|~D)	**30.54%**
False - rate for true D	Pr(-| D)	**31.45%**
False + rate for classified +	Pr(~D| +)	**71.34%**
False - rate for classified -	Pr(D| -)	**7.50%**
Correctly classified		**69.32%**

A11 - *Estat classification* results for Model 3, with relevant probability cut-off

Logistic model for mentalill

Classified	True D	True ~D	Total
+	**1872**	**4586**	**6458**
-	**843**	**10579**	**11422**
Total	**2715**	**15165**	**17880**

Classified + if predicted Pr(D) >= .1533768
True D defined as mentalill != 0

Sensitivity	Pr(+| D)	**68.95%**
Specificity	Pr(-|~D)	**69.76%**
Positive predictive value	Pr(D| +)	**28.99%**
Negative predictive value	Pr(~D| -)	**92.62%**
False + rate for true ~D	Pr(+|~D)	**30.24%**
False - rate for true D	Pr(-| D)	**31.05%**
False + rate for classified +	Pr(~D| +)	**71.01%**
False - rate for classified -	Pr(D| -)	**7.38%**
Correctly classified		**69.64%**

A12 - *Estat classification* results for Model 4, with relevant probability cut-off

```
Logistic model for mentalill

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |      1870          4671  |       6541
     -     |       845         10494  |      11339
-----------+--------------------------+-----------
   Total   |      2715         15165  |      17880

Classified + if predicted Pr(D) >= .1496353
True D defined as mentalill != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   68.88%
Specificity                     Pr( -|~D)   69.20%
Positive predictive value       Pr( D| +)   28.59%
Negative predictive value       Pr(~D| -)   92.55%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)   30.80%
False - rate for true D         Pr( -| D)   31.12%
False + rate for classified +   Pr(~D| +)   71.41%
False - rate for classified -   Pr( D| -)    7.45%
--------------------------------------------------
Correctly classified                        69.15%
--------------------------------------------------
```

A13 - The part of the FHI questionnaire that we received

2.1: Are you married/have a domestic partner, single or do you have boyfriend/girlfriend?

- Married/Registered partner
- Domestic partner
- Have a boyfriend/girlfriend (that you dont live with)
- Single

2.2 How many people (including you) live in your household?

2.2b: How many children under the age of 18 are you in the care of? (Only shows up if the respondent answered 2 or more on question 2.2.

2.3: What work- or lifesituation are you in?

- Working full time (32 or more hours per week)
- Working part time (32 or less hours per week)
- Self-employed
- On furlough
- On sick leave
- Unemployed
- On disability
- Receiving social assistance

- On pension
- In school
- Conscripted in the military
- Stay at home parent

2.4: What is your highest completed education?

- Primary school/ “Folk High School”
- High school / Vocational education minimal 3 years
- College / University up to 4 years
- College / University 4 years or more

2.5: If living alone: Think about your total income. If living with others, think about the total income for the whole household. How easy or hard is it for you to make ends meet, with this income?

- Very hard
- Hard
- Fairly hard
- Fairly easy
- Easy
- Very easy
- Don’t know

3.1: Have your work situation changed as a result of the covid pandemic?

- Yes
- No
- Is not working

Think back to the time in June this year (2020).
9.1: All in all, how satisfied were you with your life at this time? Rate from 0-10"
9.2: To what degree were you worried in dailylife at this time? Rate from 0-10
9.3: To what degree were your social relations rewarding and supportive at this time?

11.1: All in all, how do you consider your own health?

- Very good
- Good
- Neither good or bad
- Bad
- Very bad

11.2: To what degree have you been bothered by these feelings the last 14 days? (HSCL-5)
1. Feeling of nervousness and inner turmoil the last 14 days:

- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days

- Bothered very much last 14 days

2. Fear or distress the last 14 days:
- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

3. Felt hopeless regarding the future the last 14 days:
- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

4. Depressed or heavy minded last 14 days
- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

5. Worried or anxious last 14 days
- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

2.1: Are you married/have a domestic partner, single or do you have a boyfriend/girlfriend?
- Married/Registered partner
- Domestic partner
- Have a boyfriend/girlfriend (that you dont live with)
- Single

2.2 How many people (including you) live in your household?

2.2b: How many children under the age of 18 are you in the care of? (Only shows up if the respondent answered 2 or more on question 2.2.

2.3: What work- or lifesituation are you in?
- Working full time (32 or more hours per week)
- Working part time (32 or less hours per week)
- Self-employed
- On furlough
- On sick leave
- Unemployed
- On disability
- Receiving social assistance

- On pension
- In school
- Conscripted in the military
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2.4: What is your highest completed education?

- Primary school/ “Folk High School”
- High school / Vocational education minimal 3 years
- College / University up to 4 years
- College / University 4 years or more

2.5: If living alone: Think about your total income. If living with others, think about the total income for the whole household. How easy or hard is it for you to make ends meet, with this income?

- Very hard
- Hard
- Fairly hard
- Fairly easy
- Easy
- Very easy
- Don’t know

3.1: Have your work situation changed as a result of the covid pandemic?

- Yes
- No
- Is not working

Think back to the time in June this year (2020).
9.1: All in all, how satisfied were you with your life at this time? Rate from 0-10"
9.2: To what degree were you worried in dailylife at this time? Rate from 0-10
9.3: To what degree were your social relations rewarding and supportive at this time?

11.1: All in all, how do you consider your own health?

- Very good
- Good
- Neither good or bad
- Bad
- Very bad

11.2: To what degree have you been bothered by these feelings the last 14 days? (HSCL-5)
1. Feeling of nervousness and inner turmoil the last 14 days:

- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

2. Fear or distress the last 14 days:

- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

3. Felt hopeless regarding the future the last 14 days:

- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

4. Depressed or heavy minded last 14 days

- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

5. Worried or anxious last 14 days

- Not bothered last 14 days
- A little bothered last 14 days
- Bothered quite a lot last 14 days
- Bothered very much last 14 days

<u>A14 - OR’s and marginal effects for our Benchmark model:</u>

Benchmark Model						
Coefficients	Odds ratio	Standard error	P >|z|	Marginal effect	Standard error	P >|z|
Intercept	0.0688	0.0048	0.000	-	-	-
oslobergen	1.5619	0.0737	0.000***	0.0501	0.0053	0.000***
female	1.6370	0.0786	0.000***	0.0553	0.0053	0.000***
higheredu	0.9237	0.0458	0.107	-0.0090	0.0056	0.107
single	1.3746	0.0902	0.000***	0.0357	0.0074	0.000***
age18_24	3.9551	0.3322	0.000***	0.1548	0.0093	0.000***
age25_44	2.5060	0.1385	0.000***	0.1544	0.0061	0.000***
age65_74	0.5472	0.0552	0.000***	-0.0677	0.0113	0.000***
age75over	0.6833	0.1179	0.027*	-0.0428	0.0194	0.027*
childund18	0.8472	0.0224	0.000***	-0.0186	0.0030	0.000***
challeco	2.9113	0.1598	0.000***	0.1200	0.0060	0.000***
withoutwork	2.2218	0.1620	0.000***	0.0897	0.0081	0.000***
* p<0.05, ** p<0.01, *** p<0.001						
N = 17 880						
Pseudo R^2 = 0.1308						
Nagelkerke R^2 = 0.184						
Cox & Snell R^2 = 0.106						

A15: OR's for Model 2, that includes "female_age18_24". From Stata.

```
. logistic mentalill female age18_24 female_age18_24 age25_44 age65_74 age75over oslobergen childund18 challec
> o withoutwork higheredu single, vce(robust)

Logistic regression                             Number of obs     =     17,880
                                                Wald chi2(12)     =    1727.24
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -6616.5787               Pseudo R2         =     0.1311

------------------------------------------------------------------------------
                |               Robust
      mentalill | Odds Ratio   Std. Err.      z    P>|z|     [95% Conf. Interval]
----------------+-------------------------------------------------------------
         female |   1.580134   .0780118     9.27   0.000     1.434399    1.740677
       age18_24 |   3.116817   .4350774     8.14   0.000     2.370784    4.097612
female_age18_24 |   1.404394   .2202903     2.17   0.030     1.032693    1.909882
       age25_44 |   2.508299   .1384643    16.66   0.000      2.25108     2.79491
       age65_74 |    .546227   .0550391    -6.00   0.000     .4483365    .6654911
      age75over |   .6791666   .1171163    -2.24   0.025     .4843889    .9522665
     oslobergen |   1.564627   .0738592     9.48   0.000     1.426361    1.716297
     childund18 |     .84781   .0223933    -6.25   0.000     .8050367     .892856
       challeco |    2.90238   .1594047    19.40   0.000     2.606181    3.232243
    withoutwork |   2.231289   .1626027    11.01   0.000     1.934307    2.573867
      higheredu |   .9230784   .0457381    -1.62   0.106     .8376487    1.017221
         single |   1.387996    .091474     4.97   0.000     1.219807    1.579376
          _cons |   .0701032   .0049498   -37.64   0.000     .0610431    .0805079
------------------------------------------------------------------------------
```

-

A16: Margins for Model 2 , that includes "female_age18_24". From Stata.

```
. margins, dydx(*)

Average marginal effects                        Number of obs     =     17,880
Model VCE    : Robust

Expression   : Pr(mentalill), predict()
dy/dx w.r.t. : female age18_24 female_age18_24 age25_44 age65_74 age75over oslobergen childund18 challeco
               withoutwork higheredu single
```

	dy/dx	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
female	.0513124	.0055401	9.26	0.000	.040454	.0621708
age18_24	.1275002	.0156338	8.16	0.000	.0968586	.1581419
female_age18_24	.0380888	.0175689	2.17	0.030	.0036544	.0725232
age25_44	.1031391	.0060941	16.92	0.000	.0911949	.1150833
age65_74	-.067823	.0113141	-5.99	0.000	-.0899982	-.0456478
age75over	-.0433919	.0193467	-2.24	0.025	-.0813106	-.0054731
oslobergen	.0502063	.005268	9.53	0.000	.0398811	.0605315
childund18	-.0185168	.0029471	-6.28	0.000	-.0242931	-.0127405
challeco	.1195056	.0060077	19.89	0.000	.1077308	.1312804
withoutwork	.090014	.00813	11.07	0.000	.0740796	.1059485
higheredu	-.0089771	.0055557	-1.62	0.106	-.0198661	.0019119
single	.0367716	.007378	4.98	0.000	.022311	.0512321

-

A17: OR's for Model 4, that includes "age18_24_challeco". From Stata.

```
. logistic mentalill age18_24 challeco age18_24_challeco age25_44 age65_74 age75over oslobergen childund18 wit
> houtwork higheredu single female, vce(robust)

Logistic regression                             Number of obs     =     17,880
                                                Wald chi2(12)     =    1736.74
                                                Prob > chi2       =     0.0000
Log pseudolikelihood = -6617.8497               Pseudo R2         =     0.1310
```

mentalill	Odds Ratio	Robust Std. Err.	z	P>|z|	[95% Conf.	Interval]
age18_24	4.242497	.4021999	15.24	0.000	3.523103	5.108786
challeco	3.006549	.1769727	18.70	0.000	2.67895	3.37421
age18_24_challeco	.7874629	.1242695	-1.51	0.130	.5779657	1.072897
age25_44	2.505052	.1386977	16.59	0.000	2.24744	2.792193
age65_74	.5486259	.0553352	-5.95	0.000	.450218	.6685436
age75over	.6848187	.1181871	-2.19	0.028	.4882856	.9604556
oslobergen	1.562414	.0736089	9.47	0.000	1.424604	1.713555
childund18	.8460801	.0224319	-6.30	0.000	.8032371	.8912082
withoutwork	2.210461	.1616352	10.85	0.000	1.915317	2.551086
higheredu	.92549	.0458756	-1.56	0.118	.8398051	1.019917
single	1.360632	.0898412	4.66	0.000	1.195464	1.548619
female	1.639394	.076887	10.54	0.000	1.495417	1.797233
_cons	.0683445	.0048253	-38.00	0.000	.0595123	.0784875

-

A18: Margins for Model 4, that includes "age18_24_challeco". From Stata.

```
. margins, dydx(*)

Average marginal effects                          Number of obs     =     17,880
Model VCE     : Robust

Expression    : Pr(mentalill), predict()
dy/dx w.r.t. : age18_24 challeco age18_24_challeco age25_44 age65_74 age75over oslobergen childund18
               withoutwork higheredu single female

------------------------------------------------------------------------------------
                  |            Delta-method
                  |      dy/dx   Std. Err.      z    P>|z|     [95% Conf. Interval]
------------------+-----------------------------------------------------------------
         age18_24 |   .1623194   .0105133    15.44   0.000     .1417137    .1829251
         challeco |    .123641   .0064754    19.09   0.000     .1109494    .1363326
age18_24_challeco |  -.0268376   .0177346    -1.51   0.130    -.0615968    .0079216
         age25_44 |   .1031445   .0061192    16.86   0.000      .091151    .1151379
         age65_74 |    -.06743   .0113416    -5.95   0.000    -.0896592   -.0452008
        age75over |  -.0425245   .0193909    -2.19   0.028     -.08053    -.004519
       oslobergen |   .0501207   .0052651     9.52   0.000     .0398013    .0604402
       childund18 |  -.0187733   .0029621    -6.34   0.000    -.0245788   -.0129678
      withoutwork |   .0890923   .0081706    10.90   0.000     .0730782    .1051065
        higheredu |  -.0086972   .0055659    -1.56   0.118    -.0196061    .0022118
           single |   .0345888   .0074049     4.67   0.000     .0200756    .0491021
           female |   .0555227   .0052549    10.57   0.000     .0452232    .0658222
------------------------------------------------------------------------------------
```