When the Economy is Hit, so is She?

An Empirical Analysis of the Consequences of the Oil Price Shock in 2014 on Domestic Violence in Norway

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Abstract

This paper examines how the regional economic downturn following the oil price shock in 2014 affected domestic violence in Norway. In particular, we exploit the fact that the economic downturn in Norway following the oil price decline was largely regional. The counties that were hardest hit by the economic downturn following the oil price decline were the counties with the highest proportion of their workforce working in oil-related industries.

We use a differences-in-differences strategy to identify the causal effects, and find that the number of people seeking counselling at domestic violence shelters increased in counties that were hit hard by the economic downturn. Specifically, we find that the regional economic downturn led to an additional 9.97 shelter users per 100,000 people each quarter in oil-dependent counties. This equals a 26 percent increase compared to the mean number of people seeking counselling at domestic violence shelters before the economic downturn. We also examine the effect of the downturn on the number of people living temporarily at domestic violence shelters. The findings indicate a modest increase, but the significance of the estimates are highly dependent on the model specification. We are therefore careful to conclude whether or not the regional economic downturn had an effect on people living temporarily at shelters.

Acronyms

AKU	The Labour Force Survey
Bufdir	The Norwegian Directorate for Children, Youth and Family Affairs
DiD	Differences-in-Differences
OLS	Ordinary Least Squares
OVB	Omitted Variable Bias
JD	Ministry of Justice and Public Security
NAV	Norwegian Labour and Welfare Administration
SSB	Statistics Norway
WHO	World Health Organization
WLS	Weighted Least Squares

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1 Introduction

1.1 Motivation and Purpose

Domestic violence is a substantial public health issue that occurs among all classes of society (Rasmussen, Strøm, Sverdrup, and Vennemo, 2015). The consequences for the victims are detrimental, and domestic violence might lead to loss of lives, reduced life quality and reduced ability to participate actively in society. In addition, domestic violence has implications for social costs through increased demand for health services, police services, legal services etc. (Rasmussen et al., 2015). A socio-economic report by the Ministry of Justice and Public Security (JD) estimated that the cost of domestic violence in Norway amounted to between 4.5 and 6 billions NOK in 2010 (Rasmussen et al., 2015). Furthermore, from 2010 to 2016, the number of domestic abuse cases reported to the police increased with 79 percent (Bufdir, 2017b).

From time to time, domestic violence becomes a hot topic in the media. For instance, the media flourished with articles about fear of increased levels of domestic violence during the FIFA World Cup in the summer of 2018. A campaign in England argued that domestic abuse rates increase by 38 percent when England loses a match (Rahman, 2018). In Norwegian media, an article from 2016 claimed that the levels of domestic violence increased as a consequence of the oil price shock in 2014 (Lygren and Hetland, 2016). Despite the sporadic media coverage, there is little empirical evidence exploring the causes of domestic violence, particularly within economic literature. This thesis aims to add to the literature by investigating how the economic downturn following the oil price shock in 2014 affected levels of domestic violence in Norway.

We use a differences-in-differences strategy and exploit the oil price shock in 2014 and the subsequent regional economic downturn that caused a considerable increase in the unemployment rate in some Norwegian counties. We contrast the development in the levels of domestic violence in counties that were hit hard by the regional economic downturn with counties where the oil price shock had less of an impact. More specifically, we compare counties with a high and a low share of the workforce employed in direct oil related industries. The increased unemployment from 2014 to 2015 is highly correlated with the share of the workforce employed in the oil sector. Thus, by using an exogenous shock to unemployment and controlling for time and county specific effects, our estimates give the causal effect of the regional economic downturn on the levels of domestic violence.

We use data from The Norwegian Directorate for Children, Youth and Family Affairs (Bufdir) and measure domestic violence as the number of users of domestic violence shelters per 100 000 people. A domestic violence shelter is a place where victims of domestic violence can receive counselling or live temporarily. Hereafter, we refer to people receiving counselling as *day users*, people receiving counselling for the first time as *new day users* and people staying overnight as *residents*. We conduct separate analyses on the impact of the regional economic downturn on these three groups.

We find that the regional economic downturn in 2014 led to an increase in the levels of domestic violence in counties with a high share of the population employed in direct oil related services. More specifically, we find that the downturn led to a 26 percent increase in the number of day users in Rogaland, Møre og Romsdal and Vest-Agder. Our findings on those living temporarily at shelters might indicate that the economic downturn led to a small increase in the number of residents, but the significance of the estimates are highly dependent on the model specification. For the number of new day users, we find no significant effect of the economic downturn.

1.2 Research Question

As the economic literature on domestic violence is fairly limited, we were motivated to study possible drivers of domestic violence. In particular, we wanted to study how economic downturns affect domestic violence. We have investigated the effect of the economic downturn in Norway following the oil price decline in 2014. As Norway is a large producer of oil, the Norwegian economy was hit hard by the oil price shock in 2014 and the reduced oil price led to increased unemployment in several Norwegian counties. Thus, the aim of this thesis is to investigate the following research question:

How did the regional economic downturn following the oil price shock in 2014 affect domestic violence in Norway?

The paper is structured in the following way: First, we give a brief overview of the prevalence of domestic violence in Norway, the role of domestic violence shelters and the impact of the regional economic downturn in section 2. Then, we present previous relevant research in section 3. In section 4 we give an overview of our data, and in section 5 we expand on our empirical strategy. Our results are presented in section 6, and section 7 discusses the findings and limitations of our paper. Lastly, our conclusion is presented in section 8.

2 | Background

2.1 Prevalence of Domestic Violence in Norway

The Norwegian Police Service defines domestic violence as "all types of physical and emotional abuse of current or former family members, and its victims include the child witnesses" (Norwegian Police Service, 2018). Previously one used the term woman abuse instead of domestic violence as there is a significantly higher proportion of female victims of partner violence compared to male victims (JD, 2013b). However, to emphasize that men, women and children could be victims of domestic violence, the term woman abuse has been replaced by the gender neutral term domestic violence (JD, 2013b).

It is challenging to quantify the exact number of victims of domestic violence, and an extensive number of incidents go unreported (JD, 2013a). According to a report made on behalf of the Ministry of Justice and Public Security in 2012, around 2 to 4 percent of the Norwegian population were victims of domestic violence (Rasmussen et al., 2015). Extrapolating these estimates to the current population implies that around 105.000 to 210.000 people were victims of domestic violence in Norway in 2018.

Domestic violence is a criminal offence in Norway, and the penalty can be imprisonment for up to 15 years according to the Penal Code § 282 (2005). However, only a fraction of domestic violence cases are reported to the police, and only a minority of the reported cases are solved (JD, 2013b) (Aas, 2013).

2.2 Domestic Violence Shelters

Domestic violence shelters have for the last 40 years been the main place where victims of domestic violence in Norway can seek help (JD, 2013b). On January 1 2010, the Crisis Centre Act came into force and made it mandatory for all Norwegian municipalities to provide necessary support to victims of domestic violence (Bufdir, 2015b).

Domestic violence shelters offer two main services. Those who seek help at a shelter can receive counselling from a shelter employee, where they can get information about i.e. statutory rights to assistance, help to contact relevant agencies or assistance during a re-establishment phase (The Secretariat of the Shelter Movement, 2018). The shelters are also obligated to provide a safe and free place where victims can live temporarily, for shorter or longer periods (The Secretariat of the Shelter Movement, 2018). Hereafter, we will refer to the people who only seek counselling as *day users*, those seeking counselling for the first time as *new day users* and those staying overnight as *residents*.

In 2017 there were 47 domestic violence shelters in Norway which served 2434 unique day users and 1806 unique residents. In total there were 10 620 day users and 69 643 overnight stays. The majority of both day users and residents are women, and in most cases the abuser is the spouse or the partner of the victim. Among the residents there is a larger proportion of victims with immigrant background compared to the day users. 66 percent of the residents in 2017 had immigrant background while the same share was only 46 percent for day users (Bufdir, 2018). In conversation with Bufdir they explained that ethnic Norwegian victims of domestic violence often have family or friends they can stay with if they need to hide from their abuser. Victims with immigrant background might have their family and friends in another country, and so they are more often in need of using residential services at the shelters. More descriptive statistics will be presented on the users of domestic violence shelters in section 4.

2.3 The Regional Economic Downturn

The price of crude oil was stable at around \$100 per barrel from 2009 to 2014. However, during the summer of 2014 the price dropped steeply, and it continued to fall throughout the rest of the year. In January 2016 the price reached its lowest point at \$30 per barrel (Macrotrends, 2018).

The falling oil price was driven by both increased supply of oil, particularly supply of shale oil from the US, and by lower international demand for oil. The economies of industrialized countries who are net importers of oil, like most countries in Europe, are stimulated by falling oil prices as they get cheaper factor inputs. The European Commision's Economic Forecast stated in the spring of 2015 that the European economy was boosted by tailwind factors such as low oil prices (European Commision, 2015).

Some industries in Norway benefited from the low oil price. However, there is no doubt that the net effect for Norway as a net exporter of oil was negative. Lower activity in the oil sector had spillover effects like reduced demand from mainland Norway, pulling in the direction of a cyclical downturn (Rogne, 2015).

The economic downturn following the oil price shock was mainly regional, and not all Norwegian industries were negatively affected by the price decline. Regions on the South and West Coast were hit hardest, as a high proportion of the population in those regions work in the oil and gas industry. From mid 2014 and up until 2016, 22.000 jobs disappeared within extraction of oil and gas, including in oil services and in the shipyard industry. (Hvinden and Nordbø, 2016) However, in the same period Norway experienced a net employment growth of 23.000 jobs (Hvinden and Nordbø, 2016).

The relation between the share of oil related jobs in each Norwegian county and the change in the county's unemployment rate is shown in figure (2.1). The figure clearly shows that when the oil price dropped, the unemployment rate rose sharply in counties with a high share of oil jobs. One can also see that some of the counties with a low share of oil jobs actually experienced reduced unemployment rates following the oil price shock. Thus, it is clear that the oil price shock caused an economic downturn in some Norwegian regions, but not at the national level.

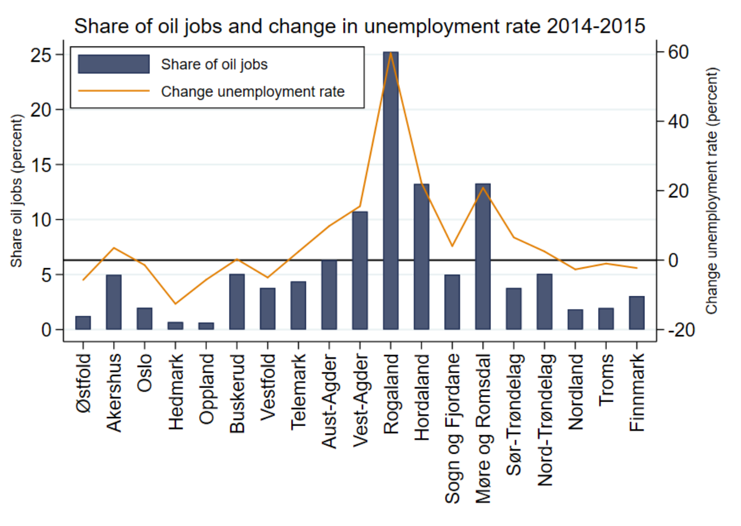

Figure 2.1: Share of oil jobs in 2014, and change in unemployment rate from 2014 to 2015
Source: Blomgren et al., 2015 and NAV

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3 | Literature Review

There is growing attention to the economic implications of abuse, but there are currently few papers on the topic (Anderberg, Rainer, Wadsworth, and Wilson, 2015). The following section reviews the literature about domestic violence that we found most relevant for our paper.

The economic literature mainly focuses on two different ways of explaining domestic violence. One part of the literature focuses on a household bargaining model, where domestic violence is seen as both intentional and rational behaviour from persons with a predisposition for being abusive. The other part of the economic literature sees domestic violence as unintentional, and being the result of certain triggers, such as negative emotional cues. Some of the economic literature also examines if changed levels of domestic violence could be explained by the theory of exposure reduction developed by criminologists.

3.1 Domestic Violence - A Holistic Approach

Before we dive into the economic literature on domestic violence, we will take a broader perspective and look at how the World Health Organization (WHO) explains abuse.

The WHO and an increasing number of researchers explain abuse as the result of the interplay of "factors at four levels - the individual, the relationship, the community, and the societal" (WHO, 2018)(Garcia-Moreno, Jansen, Heise, and Watts, 2005). The interplay can be depicted as a set of circles where each circle represents factors that might increase or reduce the likelihood of violence, as seen in figure (3.1). The innermost circle represents individual factors, such as psychological disorders, predisposition of abuse of alcohol or other substances. The second circle represents relational factors, for example may having violent friends or an experience of bad parenting increase the likelihood of violent behaviour. The third circle represents the context of communities where relationships take place. Poverty, high unemployment rate and high prevalence of drugs are examples of risk factors at the third level which may increase the likelihood of violent behaviour. The fourth circle represents societal factors such as norms and policies. This paper will mainly focus on the third circle, the community level, as we aim to investigate whether a regional economic downturn impacts the level of domestic violence.

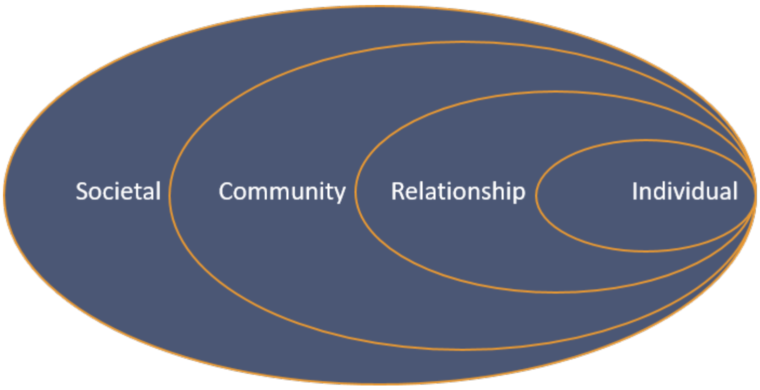

Figure 3.1: Factors explaining abuse - WHO
Source: Reproduced from Garcia-Moreno et al., 2005

3.2 Domestic Violence and Household Bargaining

Aizer (2010) provides the first causal estimates of the impact of women's relative wage on levels of domestic violence. In the paper, Aizer finds empirical evidence for a causal relationship between the gender wage gap and the levels of woman abuse. She uses data on female hospitalizations for assault in the US state of California for the period 1990 to 2003, where there had been a decline in the number of hospital admissions for assaults. Specifically, she finds that reductions in the gender wage gap can explain 9 percent of the decline in domestic violence.

Aizer analyzes the different mechanisms driving her result, and initially believes that the reduction in domestic violence can be explained by either a household bargaining model or the theory of exposure reduction. First she tests whether the results can be explained by exposure reduction. This channel was suggested by the criminologists Dugan, Nagin and Rosenfeld (1999), and posits that an increase in either male or female employment will reduce domestic violence because increased employment reduces the time partners spend together. Aizer believes this could be a possible channel because an increase in women's relative wage is likely to be accompanied by an increase in female employment. The findings of Aizer are however inconsistent with the theory of exposure reduction, as she finds that the reductions in domestic violence happen during non-work hours. Secondly, Aizer tests the predictions of an economic theory of household bargaining that incorporates violence. The model predicts that an increase in a woman's relative wage increases her bargaining power and lowers the level of domestic violence due to an improvement of her options outside the household. Aizer finds empirical evidence for the household bargaining model, and concludes that there is a causal relationship between relative labour market conditions and domestic violence.

Based on the model of household bargaining power, Anderberg et al. (2015) hypothesize on the effect of unemployment on domestic violence. They extend the model by including gender-specific unemployment risks, and predict that an increase in male unemployment decreases the levels of domestic violence and vice-versa. The argument is that males with a predisposition for abusive behaviour may abstain from violence if they are afraid of losing their job, because they have an economic incentive to keep their spouse. In this way, refraining from abusive actions or being abusive can be understood as the result of rational reasoning. By using data on partner abuse against women in England and Wales, they find that the overall unemployment rate has no significant effect on domestic violence. This is consistent with previous findings. They do, however, find that gender specific unemployment rates affect domestic violence. Their findings suggest that a 1 percentage point increase in the male unemployment rate causes a 3 percent decline in the number of incidents of domestic violence against women. Furthermore, they find that a similar increase in the female unemployment rate will have the exact opposite effect, causing an increase in domestic violence against women.

3.3 Potential Triggers of Domestic Violence

Some literature suggests that domestic violence can be understood as unintentional acts triggered by different factors. Card and Dahl (2009) set forth that negative emotional cues can lead to loss of control which in turn increases the likelihood of violent behaviour. They find that when the home team in the National Football League loses a match they were expected to win, the number of police reports of domestic partner violence executed by men increase by 8 percent. However, if the home team loses a match they were expected to lose, they find only a minimal increase in the number of police reports. Furthermore, Card and Dahl find that if the home team wins a match they were expected to lose, there is at most a small reduction in domestic violence. This is consistent with the behavioral prediction of loss aversion - losses matter more than gains.

Another potential trigger for domestic violence is alcohol abuse. Angelucci (2008) examines the social implications of the social welfare program *Oportunidades* which increased the average income of wives in Mexico by on average \$20 a month. Angelucci finds that the program caused a 15 percent reduction in alcohol abuse for all households, but that the effect on household violence varied. For households entitled to a minimum transfer, and for households where the husband had completed primary school, household violence decreased by 37 percent. The paper links this reduction in household violence to the reduction in alcohol abuse. However, the effect was not clear, and among uneducated men married to younger women the transfers led to an increase in violence.

3.4 Implications for our Study

The literature explaining domestic violence using a household bargaining model postulates that increased levels of male unemployment reduce the levels of domestic violence. The oil sector in Norway has been dominated by men for the past 10 years (Haaland, 2018), and as male unemployment rose more than female unemployment following the oil price shock in 2014 one might expect domestic violence to have been reduced. However, the picture is not clear as the development of the ratio between male and female unemployment differs between the counties that were hardest hit by the oil price shock. The unemployment rates can be seen in the figures in section

(A.5) in the Appendix.

The literature on exposure reduction predicts that an increase in the overall unemployment rate leads to increased levels of domestic violence as people in violent relationships get more exposed to their violent partner. The regions that were hit hardest by the regional economic downturn experienced a sudden increase in the overall unemployment rate. One might therefore expect that the regional economic downturn caused an increase in the levels of domestic violence. The belief that increased exposure to a violent partner increases the levels of domestic violence is also held by workers at domestic violence shelters, as shelters experience a greater influx of people during holidays (Lygren and Hetland, 2016).

We argue that the theory of exposure reduction is particularly applicable to our case due to the nature of the work of the people who became unemployed during the downturn. Many people in the oil sector work shifts on platforms, where they typically work for two weeks before they stay home for three or four weeks (Exsto Offshoreutdanning AS, 2018). When these people lose their job, they suddenly spend significantly more time at home. The consequence is that spouses of people with violent tendencies who lose their job spend more time with their violent partner.

Even though the theory of household bargaining and the theory of exposure reduction seemingly predict opposite outcomes of the economic downturn, they are not necessarily contradictory. The downturn might have caused some men to refrain from violent behaviour because they had an economic incentive to keep their wife, as the household bargaining model predicts. At the same time, the frequency of violence might have increased when people with violent tendencies spend more time with their partners, as the exposure theory predicts. However, as we look at the data on an aggregated level, we will not be able to separate these two effects. It is therefore difficult to make predictions on the aggregated effect of the economic downturn on the levels of domestic violence in our case.

4 | Data

We use panel data on the number of users at each domestic violence shelter in Norway in order to investigate the effect of the regional economic downturn on the levels of domestic violence. We have also collected data to create control variables. Furthermore, we use county level data on unemployment and on the share of the workforce working in the oil sector to decide how hard counties were hit by the regional economic downturn.

4.1 Domestic Violence Shelter Data

The main data contains information about the users of domestic violence shelters in the period 2012 to 2016 and comes from the The Norwegian Directorate for Children, Youth and Family Affairs (Bufdir). When a person seeks help at a domestic violence shelter they are registered by an employee at the shelter, and they are encouraged to fill out a questionnaire. The questionnaire asks for background information about the victim, like their marital status, employment status and age. Because the people seeking help are not obligated to fill out the questionnaire, we only have background information on some users. More specifically we have background information on approximately 30 percent of the day users and 94 percent of the residents.

We transform the data to take into account the size differences in population between Norwegian counties and the size differences between the domestic violence shelters. Our final variable measures the quarterly number of day users or residents per 100,000 people in the county. To calculate the variable, we merged the quarterly number of users from domestic violence shelters in each county. Then, we multiplied the quarterly number of users in each county by 100,000, and divided the number by the total population in the county, using data from Statistics Norway, (SSB).

Previous research have measured domestic violence as, for instance, the number of female hospitalizations for assault and the number of police reports of family violence. However, only a fraction of domestic violence cases are reported to the police, and female hospitalization might only capture the most severe cases of domestic violence. We measure domestic violence as the number of shelter users, and we believe our measure has several advantages as a source of information on domestic violence. Firstly, the victims do not themselves have to report the abuse as they are automatically registered when they visit a shelter. Secondly, the data contains information on women from all parts of society and the users cannot abstain from being registered. Thirdly, the data is consistently collected.

A limitation to our data is that it is voluntary for the employees at domestic violence shelters to register the users. This implies that we do not have data on everyone who used shelter services. This could be a problem to the analysis if some shelters became systematically better or worse at registering their users after the regional economic downturn. However, Bufdir informed in an email that they believe that most users are registered. Bufdir did also inform that the shelters' incentive for registering the users is to document their work and direct attention to the problem of domestic violence.

Shelters are not obligated to register their users, and it is therefore possible that the registering could be affected by the way the shelters are funded. All shelters are funded by lump sums (Ministry of Finance, 2018), and according to Bufdir the funding structure of the shelters have not changed in the period we examine. Thus, there is no reason to believe that funding should have a significant impact on whether users are registered or not.

4.2 Unemployment Data

There are two different measures of the unemployment rate in Norway. One measure is derived from the number of people who are registered as unemployed at the Norwegian Labour and Welfare Administration (NAV). People registered as unemployed at NAV receive unemployment benefits. To be eligible for benefits one cannot have any form of paid employment, one must have tried to get a job and one must be able to work (NAV, 2018). The other measure of unemployment is derived from the Labour force survey (AKU).

The unemployment measure from AKU is a broader measure than the one from NAV, because it also includes unemployed people who do not receive benefits. Thus, the unemployment rate calculated from the AKU-data is typically higher than the unemployment rate calculated from NAV-data.

We have collected data from SSB on the number of people who are registered as unemployed at NAV. The reason we only use these numbers is that the AKU-data was not available at county-level, and we are interested in comparing the unemployment rate between Norwegian counties.

4.3 Share of Workforce in the Oil Sector

A report by Blomgren et al. (2015) presents numbers on the share of oil related jobs in Norwegian counties from 2014. More specifically, they present two different measures: The first measure is the share of the workforce working in both direct and indirect oil related industries. The second measure only includes the share of the workforce working in direct oil related industries. The direct oil related industries captures those who work offshore, for operator companies or with supply to the oil industry (Blomgren et al., 2015). The indirect oil related industry is a broader term that encompasses, for instance, consultants who work on oil-related projects (Blomgren et al., 2015). In our paper we will mostly use the share of the workforce working in direct oil related industries, and this will be referred to as *oil intensity.* The reason we prefer the measure using only the share working in direct oil related industries is that it has a higher correlation with the unemployment rate following the oil price decline compared to the measure using both direct and indirect oil related industries.

we consider it to be the best proxy for how hard a county was hit by the regional economic downturn.

We use data on the counties' oil intensity for two purposes: Firstly, we use it to decide to which extent a county was affected by the oil price shock. As can be seen in figure (2.1), there is a positive correlation between the development of a county's unemployment rate from 2014 to 2015 and the county's oil intensity. Secondly, we use data on oil intensity in our empirical models to create a proxy for how hard a county was hit by the regional economic downturn.

4.4 Control Variables

We have collected variables on the level of education, the share of immigrants and the age distribution in each county.

The level of education in each county is collected from SSB. Including variables that controls for the level of education allow us to control for differences in the level of education between counties and over time.

The share of immigrants in each county is collected from SSB. An immigrant is here defined as a person with both parents originating from outside of Norway (SSB, 2014). Including this variable allows us to control for differences in the share of immigrants between counties and over time.

The data on age distribution in each county is collected from SSB. Including this variable allows us to control for differences in the age distribution between counties and over time.

4.5 Descriptive Statistics

The number of new day users have been stable from 2010 to 2017, whereas the total number of day users have increased by approx. 23 percent, as can be seen in figure A.1 in the appendix. This implies that each day user in 2010 on average visited a shelter 3,6 times, whereas in 2017 each day user visits a shelter on average 4,4 times. As shown in figure A.2 the number of unique yearly residents have decreased by approx. 12 percent form 2010 to 2017, while the number of overnight stays have been stable, implying that the number of overnight stays per resident have increased slightly.

The share of day users with immigrant background has been relatively stable at around 45 to 50 percent, see figure A.3 in the appendix. The share of residents with immigrant background has been slightly higher at around 62 to 67 percent the last couple of years, see figure A.4.

A third of both residents and day users receive either social benefits or pension, see figure A.5. Almost twice as many of the day users (approx. 30 percent) have a full-time job compared to the residents (approx. 15 percent). Another difference between the two groups is that almost twice as many of the residents (approx. 40 percent) are married compared to the day users (approx. 20 percent), see figure A.6. The majority of day users and residents are between 30 and 49 years old, see figure A.7 and figure A.8.

5 | Empirical Strategy

5.1 Differences-in-Differences

An ideal set-up would have been to compare the levels of domestic violence in Norway after the oil price shock with a counterfactual situation where the oil price shock did not happen. As this is impossible, we contrast the development of domestic violence in counties with a high versus low share of the workforce employed in direct oil related industries.

We use differences-in-differences (DiD) to find the causal effect of the regional economic downturn on the levels of domestic violence. A premise for using this method is that the treatment group and the control group share a parallel trend before the treatment takes place. Identification comes from divergence from the parallel pre-trend, and the assumption is that the treatment and the control group would have developed similarly in the counterfactual situation where the treatment had not taken place. This is a strong assumption, but it is crucial for being able to attribute the divergence of the treatment group to being the causal effect of the treatment.

The simplest setup of DiD can be depicted graphically as in figure (5.1) below. We have two time periods, the time before treatment, $t = 0$, and the time after treatment, $t = 1$. D indicates treatment and control group, $D = 1$ for the treatment group and $D = 0$ for the control group. Y represents the outcome in equation (5.1) and in figure (5.1) below. $Y(1)$ denotes the outcome in the post-treatment period and $Y(0)$ is the outcome in the pre-treatment period. The subscript indicates whether a group has actually received the treatment, so Y_1 denotes the outcome if the group has been treated while Y_0 denotes the outcome if the treatment has not taken place.

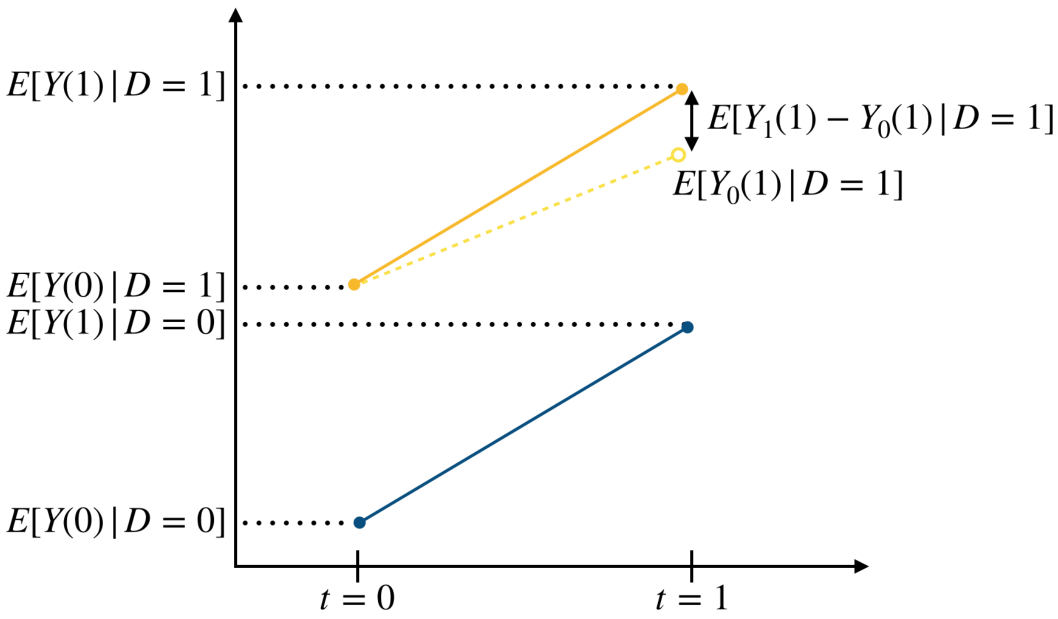

Figure 5.1: Illustration: DiD

The blue line represents the development of the control group, the orange line represents the development of the treatment group and the yellow dotted line represents how the outcome of the treatment group would have developed in absence of the treatment. Thus, the causal effect of treatment is the difference between the dotted and the yellow line as this represent the divergence of the treatment group from the parallel trend. Mathematically we can denote this as:

$$\begin{aligned} E[Y_1(1) - Y_0(1)|D = 1] = &\{E[Y_1(1)|D = 1] - E[Y_0(1)|D = 0]\} \\ &- \{E[Y_0(0)|D = 1] - E[Y_0(0)|D = 0]\} \end{aligned} \tag{5.1}$$

We can now interpret equation (5.1). The first part of the equation, $\{E[Y_1(1)|D = 1] - E[Y_0(1)|D = 0]\}$, represents the difference between the treatment and the control group in the post-treatment period. The second part of the equation, $\{E[Y_0(0)|D = 1] - E[Y_0(0)|D = 0]\}$, represents the difference between the treatment and the control group in the pre-treatment period.

5.2 Treatment and Control Group

Our choice of treatment and control group is based on four criteria: Firstly, we want our treatment group to consist of counties with an oil intensity of at least 10 percent. For the control group we require the oil intensity to be less than 2 percent. Secondly, we want our treatment group to have experienced an increase in the male unemployment rate by at least 1 percent from 2014 to 2015. For the control group we require that both male and female unemployment decreased during the same time period. Thirdly, we want our treatment and control group to have parallel pre-treatment trends, in order to fulfill the assumptions of the differences-in-differences estimation method. Lastly, the data from the counties must be reliable and of good quality.

The counties Oslo, Troms, Nordland, Østfold, Hedmark and Oppland are potential candidates for the control group as they all have an oil intensity lower than 2 percent, and they experienced reduced levels of unemployment for both males and females from 2014 to 2015. Potential candidates for the treatment group are the counties Rogaland, Hordaland, Møre og Romsdal and Vest-Agder as they all have an oil intensity above 10 percent and they experienced at least a 1 percent increase in the male unemployment from 2014 to 2015. However, Hordaland is excluded from the treatment group based on poor data quality as there was a closure of a major domestic violence shelter in 2013 and another domestic violence shelter in the county has been troubled with major internal conflicts for several years (Bergens Tidende, 2018).

When looking at the development in Hedmark and Troms (candidates for the control group), we notice that some of their shelters experienced a remarkably high growth in the number of users in the period after 2014. The domestic violence shelter in Tromsø states in their annual report from 2014 that the increase in the number of day users from 2013 to 2014 stems from hiring extra staff in order to increase capacity (Krisesenteret for Tromsø og omegn, 2015). This makes Troms not well suited as a control county, as its trend in the post-treatment period likely will differ from the pre-treatment trend even in absence of the treatment. There is a similar problem with the county Hedmark, as the growth in the registered number of day users from 2014 to 2016 at their largest shelter is caused by them changing the criteria for being registered as a day user (Hamar interkommunale krisesenter, 2016). Thus, we exclude both Troms and Hedmark from the control group.

Hence, our treatment group consists of Rogaland, Møre og Romsdal and Vest Agder, and our control group consists of Oslo, Nordland, Østfold and Oppland. A plot of these two groups along with several other plots of potential treatment and control groups are depicted in section (A.2), (A.3) and (A.4) in the appendix.

5.3 Regression Model for the Impact of the Regional Economic Downturn on Domestic Violence

To estimate the impact of the regional economic downturn following the oil price shock in 2014, we estimate the following equation:

$$Y_{ct} = \alpha + \delta_{DD}(Post_t \ \times \ Treated_c) + \lambda_c + \theta_t + \gamma_t + e_{ct} \tag{5.2}$$

Y_{ct} denotes the number of users of domestic violence shelters per 100,000 people in county c at time t. $Post_t$ is a dummy variable equal to 0 before, and 1 after the the oil price shock in 2014Q3. $Treated_c$ is a dummy variable equal to 1 if the county is in the treatment group and 0 if the county is in the control group.

We include the interaction term $(Post_t \ \times \ Treated_c)$ to uncover the true causal effect of the regional economic downturn. The coefficient that captures the causal effect, δ_{DD}, indicates the average quarterly change in the number of users of domestic violence shelters per 100,000 people in the treatment group.

λ_c represents county fixed effects, allowing for time invariant differences between counties. Differences in demography or population density are examples of characteristics that are relatively stable over time, but might differ between counties. Our analysis will suffer from omitted variable bias if these time invariant characteristics correlate with our variable of interest as well as having an impact on our outcome variable. We would then over- or underestimate the effect of the regional economic downturn on the levels of domestic violence. However, λ_c eliminates this potential bias by capturing the effect of the county specific characteristics.

θ_t represents year specific effects and γ_t represents quarter specific (seasonal) effects. θ_t and γ_t allow for time varying effects that vary between year or quarters, but are common to all counties. An example of seasonal variation might be that the level of violence increases during Christmas, such that the fourth quarter has a generally higher level of violence.

5.4 Regression Model Including Exposure to the Regional Economic Downturn

We believe that unemployment might be an important determinant of domestic violence. Thus, we want to investigate how the increased unemployment rate, following the oil price shock in 2014, affected the levels of domestic violence. However, regressing the levels of domestic violence on the unemployment rate could lead to reversed causality as there might be a two-way causal relationship between domestic violence and unemployment. Increased levels of domestic violence could affect the victims capability to work, and thus possibly increase the unemployment rate. We therefore include oil intensity as a proxy for how the unemployment were affected by the oil price shock.

There are two main reasons why a county's oil intensity is a good proxy for the increase in the county's unemployment from 2014 to 2015. First, the proxy solves the issue of reversed causality as we find it unlikely that the levels of domestic violence have an impact on the share of people working in the oil sector. Secondly, as discussed in section (2.3), there is a positive correlation between the share of employees working in direct oil related industries and the increase in the unemployment rate from 2014 to 2015. To illustrate, Møre og Romsdal with an oil intensity experienced a 13.3 percent a 20 percent increase in unemployment between 2014 and 2015, whilst Rogaland with an oil intensity of 25.2 percent experienced a 60 percent increase in unemployment. To adjust for the fact that some counties were hit harder than others by the economic downturn in 2014 we introduce a second regression model to be estimated:

$$Y_{ct} = \alpha + \delta_{DD} Exposure_{ct} + \lambda_c + \theta_t + \gamma_t + e_{ct} \tag{5.3}$$

The only difference between equation (5.2) and (5.3) is that the interaction term $Post_t \times Treated_c$ is replaced with the variable $Exposure_{ct}$. Thus, $Exposure_{ct}$ is now the variable that let us uncover the causal effect of the regional economic downturn on the levels of domestic violence. The variable is equal to zero for observations from 2012Q1 to 2014Q2. For the period after 2014Q2, the variable is equal to the share of employees in county c working in direct oil related industries. An overview of the values for the variable $Exposure_{ct}$ for $t \geq 2014Q3$ can be seen in the appendix table (A.1).

5.5 Weighted Least Squares

In the regression models (5.2) and (5.3), all observations are given the same weight, meaning observations from populous counties like Oslo are given the same weight as observations from less populous counties like Finnmark. There are however cases where we prefer to assign a higher weight to more populous counties. To achieve this we use a regression procedure called Weighted Least Squares (WLS). There are two reasons why we might want to adjust for population size.

One reason to use WLS is that the typical Norwegian citizen is more likely to live in Oslo than in Finnmark. If we do not use population weights, our estimates will be averages over counties, ignoring that the observations from Oslo are more representative for the Norwegian population than observations from Finnmark.

The second reason to use WLS is that the number of shelter users in small counties are subject to more random variation from year to year than the number of users in populous counties. The consequence is that data from populous counties are more reliable than observations from smaller counties. Thus, we may want to attach a higher weight to observations from populous counties to increase the precision of the regression estimates (Angrist and Pischke, 2015).

There are however some potential drawbacks with WLS. Because we put more weight on the populous counties, we put less weight on possibly useful variation in the small counties. There are also some technical restrictions necessary for claiming that the weighted estimates are more precise than the estimates from regular OLS. According to Angrist and Pischke (2015), the best outcome is when both the estimates and the standard errors are quite insensitive to weighting.

The regression equation for our WLS-estimation is given by the same equations as in models (5.2) and (5.3), but all the variables are multiplied by the weight $\sqrt{n_c}$. This weight is equal to the square root of the average population size in county c over the period 2012 to 2016.

5.6 Control Variables

It could be of interest to include control variables in model (5.2) and (5.3). Control variables are typically included to make the zero conditional mean assumption more likely to hold, and to control for factors that could cause the counties in the treatment and the control group to differ after treatment. The zero conditional mean assumption states that the error term must be independent of the variable of interest. If the assumption does not hold, our estimates could be biased due to omitted variables that are correlated with the variable of interest.

The control variables included in our models are related to population characteristics in the counties. The control variables are created as dummy variables that are county and time dependent, and control for education differences and age composition. The dummy controlling for education levels is equal to 1 if the share of the population in county c at time t with high school as their highest level of educational attainment is higher than the median share in the sample. Likewise, the age dummy is equal to 1 if the percentage of the population in county c at time t who are between the age of 0 and 19 is higher than the median share in the sample[1].

The reason we include the control variables as dummies and not the exact percentages themselves is that we have few observations in our sample, and thus lack variation. As can be seen in table (5.1), the population characteristics do not change much over time, and the development is similar in both the treatment and in the control group. Including the percentages themselves would be like including several time trends for the counties, and these would explain almost all the variation in the sample.

[1]We also intended to control for the percentage with immigrant background in the counties using dummy variables related to the median. Unfortunately, the values of the dummy variable were constant for each individual county. Thus, the dummy was perfectly collinear with the county fixed effects and could not be included in the regression.

The fact that we have few observations in our sample is also the reason why we prefer the regressions without control variables over the regressions where control variables are included. Because the population characteristics do not change drastically in our sample, the dummy variables controlling for these characteristics do not change much within groups either. For a majority of the counties, the control dummy variables are constant over the sample period. We do however include the control variables as a robustness check for our main results.

Table 5.1: Summary statistics

	Treatment group Pre-treatment	Treatment group Post-treatment	Control group Pre-treatment	Control group Post-treatment
Outcomes				
- Day Users	37.96	44.96	66.07	63.47
- Residents	13.03	12.95	15.29	13.50
- New Day Users	2.917	3.774	4.582	4.901
Controls				
- Migrant	10.5	12.0	11.1	12.2
- Children	26.4	25.9	23.5	22.9
- High School	45.0	42.9	40.7	39.0
- University Short	21.2	21.9	21.6	22.3
- University Long	6.09	7.09	7.66	8.66
Observations	30	30	40	40

Sources: SSB, 2018a, 2018b and 2018d

Notes: The table shows the mean value of the variables. The values denoted Outcomes are the mean quarterly number of users per 100,000 people in each county. The values denoted Controls are the mean values in percent. Migrant denotes the share of the population with both parents born abroad (SSB, 2014). Children denotes the share of the population between the age of 0 and 19. High School denotes the share of the population with upper secondary school as their highest level of education attainment. University Short denotes the share of the population with up to 4 years of higher education as their highest level of education attainment. University Long denotes the share of the population with more than 4 years of higher education.

5.7 Repercussions of the 2014-Oil Price Shock

The oil price shock in 2014 can be considered a natural experiment. From mid-2014 to the end of 2014, the oil price dropped by about 50 percent. The price drop resulted in increased unemployment in counties where a high proportion of the workforce worked in the oil sector, whereas it did not have an impact on the levels of unemployment in counties where few worked in the oil sector.

The oil price decline can be seen as an external shock to the demand for labour, and we therefore assume that the rise in unemployment post mid-2014 is unrelated to other factors that influence the levels of domestic violence. This enables us to measure the true causal effect of the increased unemployment on the levels of domestic violence.

We use data up until 2016 in our analyses because we believe there were still repercussions of the regional economic downturn by the end of that year. There are three reasons why we believe the repercussions lasted for so long. Firstly, in the Offshore Technology Days Survey, 40 percent of the largest firms in the oil industry answered that they laid people off in 2016, either permanently or temporarily (Petro.no AS, 2017). This is underpinned by the fact that the male unemployment rate increased in 2016 in most of the counties with a high proportion of the workforce employed in direct oil services. Lastly, in a news article from August 2016, a representative from the crisis shelter in Stavanger stated that several of their users needed help as a result of the regional economic downturn (Lygren and Hetland, 2016).

5.8 Parallel Trends Assumption

The key assumption for identifying a causal effect when using DiD is the assumption of parallel trends of the treatment and the control group before the treatment takes place (Angrist and Pischke, 2015). In figure (5.2), (5.3) and (5.4) we have plotted the development of the treatment and the control group using data on day users, residents and new day users respectively. The treatment group in figure (5.2) and the following plots consists of Rogaland, Møre og Romsdal and Vest-Agder, and the control group consists of Oslo, Nordland, Østfold and Oppland.

The pre-treatment development for day users in figure (5.2) looks fairly parallel. There are some periods where the magnitudes differ somewhat, or where the trends move in opposite directions like in 2013Q2. However, these deviations seem to be the exception rather than the rule, and so we conclude that the data on day users seems suitable for DiD.

The pre-treatment trends for residents plotted in figure (5.3) seem quite parallel around the cutoff, but there is a divergence in the trends at the beginning of 2012. In addition, the magnitude of the increase in the number of residents for the control group right before the cutoff is larger for the control group compared to the treatment group. However, we believe the pre-treatment trends to be adequate for DiD.

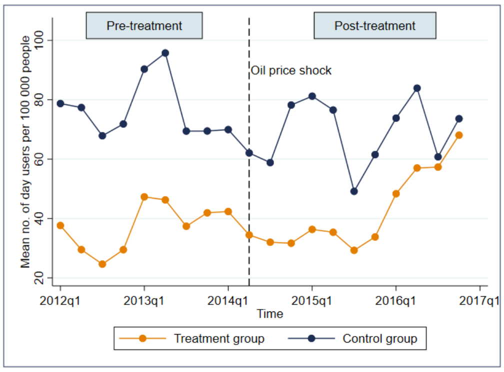

Figure 5.2: Full Sample Day Users

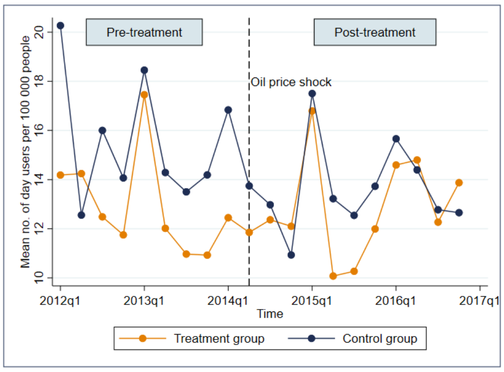

Figure 5.3: Full Sample Residents

The pre-treatment trends for new day users, plotted in figure (5.4), are clearly not parallel. The data on new day users are therefore unsuitable for DiD as the parallel trends assumption is not fulfilled.

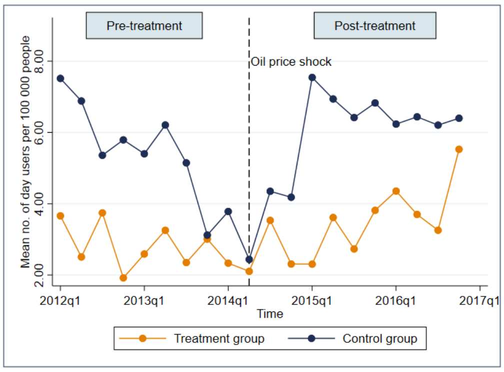

Figure 5.4: New Day Users Full Sample

6 | Empirical Analysis

Overall we find that the regional economic downturn led to a significant and substantial increase in the number of day users in counties with a high percentage of the population employed in direct oil related industries. Our results also indicate that the number of residents increased as a consequence of the oil price shock, but the significance of these results vary with different model specifications. In the following part we first present our results on day users, residents and new day users before we present the sensitivity analysis.

6.1 Results Day Users

In table (6.1) we present the results of estimating equation (5.2) using data on day users. Column (1) shows the mean number of day users for the treatment group in the pre-treatment period, and column (2) to (5) show regression results using different model specifications. Our baseline results are presented in column (2) and suggest that the regional economic downturn led to an additional 9.97 day users per 100,000 people each quarter, significant at the 1 percent level in oil intense counties. This equals a 26 percent increase from the pre-treatment mean of 37.96 day users. When introducing population weights, in column (3), the effect of the downturn becomes somewhat larger, more specifically 12.87 additional day users per 100,000 people, still significant at the 1 percent level. The estimated increased effect of the downturn could be due to Rogaland being assigned more weight while also being the county with the highest oil intensity.

Table 6.1: DiD-estimates on Day Users - Interaction term

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Including control variables	(5) Including control variables and population weights
Day Users	37.96				
Treated x Post		9.971***	12.87***	11.76***	15.61***
		(3.566)	(4.290)	(4.221)	(5.347)
Observations	30	140	140	140	140
Adjusted R^2		0.856	0.834	0.861	0.839
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of day users per 100,000 inhabitants. There are two control variables: The first control variable is a dummy variable equal to 1 if the share of the population in the county with High School as their highest educational attainment is higher than the median share in the sample. The second control variable is a dummy variable equal to 1 if the share of the population between the age of 0 and 19 is higher than the median share in the sample. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the estimates when control variables are included. Column (5) uses WLS and includes control variables.

In table (6.2) we present the results of estimating equation (5.3). This model specification takes into account that some counties were hit harder by the regional economic downturn than others by introducing the variable exposure. Our baseline results are presented in column (2). We find that the coefficient is significant at the 10 percent level, but it is worth noting that it is close to being significant at the 5 percent level as the p-value is equal to 0.052. However, the estimate itself does not have an interpretation of interest as it shows the effect of the regional economic downturn if the whole workforce were employed in direct oil related services. In order to find the effect of the regional economic downturn in a specific county, we must multiply the coefficient with the oil intensity in that county. For Rogaland, with an oil intensity of 25 percent, the estimate suggests that the regional economic downturn caused an increase of 9.84 day users per 100,000 people each quarter. This equals a 26 percent increase from the pre-treatment mean of 37.96 day users per 100,000 people. For the other two counties in the treatment group, Møre og Romsdal and Vest-Agder, we find that the regional economic downturn led to an increase of 5.19 and 4.18 day users per 100,000 people each quarter respectively.

When introducing population weights, the estimate increases to 49.13 day users per 100,000 people, significant at the 5 percent level, as can be seen in column (3). This translates to an increase of 12.4 day users per 100,000 people in Rogaland. For Møre og Romsdal and Vest-Agder we find an increase of 6.53 and 5.26 day users per 100,000 people.

We observe that the estimated coefficients and the standard errors in table (6.1) and table (6.2) change moderately when introducing population weights. Thus, we argue that our estimates are relatively insensitive to population weighting. This implies that the effect of the regional economic downturn in smaller counties are quite similar to the effect of the downturn in larger counties. The estimates also become more significant when using population weights, as smaller counties, which often have more random variation, are assigned less weight. Nonetheless, all the results indicate that the regional economic downturn that started in 2014 caused a significant and sizeable increase in the number of day users at domestic violence shelters in Rogaland, Møre og Romsdal and in Vest-Agder.

In column (4) and (5) in table (6.1) and table (6.2) we show the results of the same regressions as in column (2) and (3) respectively, but where we include the control variables mentioned in chapter (5.6). We observe that including the control variables increases the estimates, but the significance

Table 6.2: DiD-estimates on Day Users - Exposure term

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Including control variables	(5) Including control variables and population weights
Day Users	37.96				
Exposure		39.04*	49.13**	56.72*	70.80*
		(19.89)	(22.30)	(30.22)	(36.45)
Observations	30	140	140	140	140
Adjusted R^2		0.851	0.828	0.857	0.833
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of day users per 100,000 inhabitants. There are two control variables: The first control variable is a dummy variable equal to 1 if the share of the population in the county with High School as their highest educational attainment is higher than the median share in the sample. The second control variable is a dummy variable equal to 1 if the share of the population between the age of 0 and 19 is higher than the median share in the sample. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.3). Column (3) shows the estimates when running equation (5.3) with WLS. Column (4) shows the estimates when control variables are included. Column (5) uses WLS and includes control variables.

levels do not change by much. The baseline results from table (6.1) increase by approximately 18 percent and the baseline results from table (6.2) increase by approximately 45 percent when adding control variables. Even though the magnitude of the estimates increase when adding control variables, the overall tendency is the same as for our results when not using control variables.

6.2 Results Residents

In table (6.3) we present the results of estimating equation (5.2) using data on residents. Column (1) shows the mean number of residents for the treatment group in the pre-treatment period, and column (2) to (5) show regression results using different model specifications. Our baseline results are presented in column (2) and suggest that the regional economic downturn led to an additional 1.7 residents per 100,000 people per quarter in oil intense counties, significant at the 10 percent level. This equals a 13 percent increase from the pre-treatment mean of 13.03, see column (1) table (6.3). Adding population weights in column (3) increase the number of residents marginally, to 1.72 residents per 100,000 people, significant at a 5 percent level.

Table 6.3: DiD-Estimates on Residents - Interaction Term

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Including control variables	(5) Including control variables and population weights
Residents	13.03				
Treated x Post		1.703*	1.724**	1.306	1.356
		(0.861)	(0.780)	(0.996)	(0.968)
Observations	30	140	140	140	140
Adjusted R^2		0.704	0.697	0.703	0.696
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of residents per 100,000 inhabitants. There are two control variables: The first control variable is a dummy variable equal to 1 if the share of the population in the county with High School as their highest educational attainment is higher than the median share in the sample. The second control variable is a dummy variable equal to 1 if the share of the population between the age of 0 and 19 is higher than the median share in the sample. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the estimates when control variables are included. Column (5) uses WLS and includes control variables.

In table (6.4) we present results of estimating equation (5.3). To find the results of interest, the coefficient must be multiplied with the share of the population working in direct oil related services for the counties in the treatment group. Using our baseline results in column (2), we find that the regional economic downturn led to a quarterly increase of 2.46, 1.31 and 1.05 residents per 100,000 people in Rogaland, Møre og Romsdal and Vest-Agder respectively. The estimate is significant at the 5 percent level. When adding population weights in column (3) the coefficient is somewhat reduced to 8.58 residents per 100,000 people, still significant at the 5 percent level.

Column (4) and (5) in table (6.3) and (6.4) show the same regressions as in column (2) and (3) respectively, but includes control variables. The coefficient is somewhat lower compared to the baseline results, and they are not significant at any level. We trust our baseline results more than the results when including control variables. However, because estimates become insignificant when including control variables, we regard the analyses using residents as less robust compared to the analyses using day users. To conclude, the regional economic downturn seems to have had a small or insignificant effect on the number of residents at domestic violence shelters.

Table 6.4: DiD-Estimates on Residents - Exposure Term

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Including control variables	(5) Including control variables and population weights
Residents	13.03				
Exposure		9.825**	8.579**	7.262	6.641
		(4.550)	(4.036)	(7.022)	(6.539)
Observations	30	140	140	140	140
Adjusted R^2		0.704	0.696	0.702	0.694
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of residents per 100,000 inhabitants. There are two control variables: The first control variable is a dummy variable equal to 1 if the share of the population in the county with High School as their highest educational attainment is higher than the median share in the sample. The second control variable is a dummy variable equal to 1 if the share of the population between the age of 0 and 19 is higher than the median share in the sample. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.3). Column (3) shows the estimates when running equation (5.3) with WLS. Column (4) shows the estimates when control variables are included. Column (5) uses WLS and includes control variables.

6.3 Results New Day Users

Table (6.5) and (6.6) show the results of running equation (5.2) and (5.3) when using data on the number of day users who seek help from a domestic violence shelter for the first time (new day users). We want to emphasize that the parallel trends assumption is likely not fulfilled using data on new day users. Thus, the estimates should not be given a causal interpretation. We do however include the results on new day users because they might give an indication of possible channels driving our results on day users. The parallel trends assumption will be further discussed in section (7.4.1).

In table (6.5) none of the coefficients are significant, and in table (6.6) the only significant coefficient is significant at the 10 percent level. In general, the standard errors are large and it does not seem like the regional economic downturn had an effect on the number of new day users at domestic violence shelters.

Table 6.5: DiD-estimates on New Day Users - Interaction term

	(1)	(2)	(3)	(4)	(5)
	Mean Pre-treatment	Baseline Results	Including population weights	Including control variables	Including control variables and population weights
New Day Users	2.917				
Treated x Post		0.727	0.210	0.641	-0.0549
		(0.509)	(0.561)	(0.599)	(0.653)
Observations	30	140	140	140	140
Adjusted R^2		0.532	0.586	0.525	0.581
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of new day users per 100,000 inhabitants. There are two control variables: The first control variable is a dummy variable equal to 1 if the share of the population in the county with High School as their highest educational attainment is higher than the median share in the sample. The second control variable is a dummy variable equal to 1 if the share of the population between the age of 0 and 19 is higher than the median share in the sample. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the estimates when control variables are included. Column (5) uses WLS and includes control variables.

Table 6.6: DiD-estimates on New Day Users - Exposure term

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Including control variables	(5) Including control variables and population weights
New Day Users	2.917				
Exposure		3.844*	1.773	3.431	0.185
		(2.290)	(2.670)	(3.072)	(3.389)
Observations	30	140	140	140	140
Adjusted R^2		0.531	0.587	0.524	0.581
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of new day users per 100,000 inhabitants. There are two control variables: The first control variable is a dummy variable equal to 1 if the share of the population in the county with High School as their highest educational attainment is higher than the median share in the sample. The second control variable is a dummy variable equal to 1 if the share of the population between the age of 0 and 19 is higher than the median share in the sample. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.3). Column (3) shows the estimates when running equation (5.3) with WLS. Column (4) shows the estimates when control variables are included. Column (5) uses WLS and includes control variables.

6.4 Sensitivity Analysis

6.4.1 Omit Counties One at a Time

Some counties were hit harder than others by the regional economic downturn, and we therefore want to investigate how the estimates change when we leave out different counties from the treatment group. This also allow us to see how important each individual county is for our results. We run the robustness tests both on data using day users and residents, the estimates are shown in section (A.6.1) in the appendix.

Robustness tests using data on day users are consistent with our previous findings, and imply that identification does not hinge on one county. We only have three counties in our control group, which can explain why the pre-treatment mean and the size of the coefficients change moderately when a county is removed. Although the the size of the coefficients differ somewhat from the results using the full sample, they all indicate that the regional economic downturn caused an increase in the number of day users. Most estimates using equation (5.2) are significant at the 1 or 5 percent level, while the significance level varies more on the estimates using equation (5.3). This is in line with the results using the full sample.

Using data on residents, we find that when removing counties from the treatment group, the point estimates are quite similar to what we found when using the full sample. The significance level does however depend on which counties we include. The estimates are mostly insignificant when removing Rogaland and Møre og Romsdal, but become significant at the 5 percent level when removing Vest-Agder.

Overall, it seems that the results using residents are more dependent on which counties we include in the treatment group than the results on day users. In general, the results when removing counties from the treatment group are quite consistent with the results using the full sample, although the size of the point estimates differ somewhat.

6.4.2 Using Observations at Shelter Level

All Norwegian municipalities are obligated to offer domestic violence shelter services to their citizens. Typically, a domestic violence shelter is financed by several municipalities in the same county. By using the population size of the municipalities belonging to each domestic violence shelter, we have calculated the number of day users per 100,000 people for each shelter. We estimate equation (5.2) and (5.3) using this data, and use the same treatment and control group as before. The results can be seen in the appendix in table (A.8).

In the regressions, we include shelter specific fixed effects, and the population weights are based on the population in the municipalities that are covered by each domestic violence shelter. The point estimates are similar to our main results on day users, but they are only significant at the 1 percent or 5 percent level when population weights are included. This could be due to the fact that there are big differences in the sizes of the domestic violence shelters. By using population weights we put more weight on the domestic violence shelters that cover more populous areas and which are subject to less random variation.

6.5 Summary of the Results

Our results suggest that the regional economic downturn caused an increase in the number of day users at domestic violence shelters in Rogaland, Møre og Romsdal and Vest-Agder. More specifically, our baseline result suggest that the regional economic downturn led to an increase of 9.97 day users per 100,000 people each quarter in oil intense counties. When adjusting for the degree to which the counties were affected by the regional economic downturn, we find that the downturn caused an increase of 9.84, 5.19 and 4.18 day users per 100,000 people in Rogaland, Møre og Romsdal and Vest-Agder respectively.

We do not find that the regional economic downturn had an effect on the number of new day users, and so it seems that the increase in the overall level of day users is driven by day users seeking help more frequently than before. It is however important to be careful when interpreting results using new day users, as the parallel trend assumption is not fulfilled.

Our results indicate that the number of residents increased as a consequence of the regional economic downturn in counties with high oil intensity. However, the significance of these estimates are highly dependent on the model specification. Our baseline result is significant at the 10 percent level, and can be interpreted such that the downturn led to an increase of 1.7 residents per 100,000 people in the oil intense counties. The sign of the estimates are equal for all analyses using residents as the dependent variable. However, the estimates are significant at the 5 percent level when using the variable Exposure, and not significant at any level when introducing control variables. Thus, we are careful to conclude whether the regional economic downturn increased the number of residents at domestic violence shelters.

7 | Discussion

7.1 Discussion of the Results

As presented in section (3), there are several papers exploring the causes of domestic violence. Our findings suggest that the regional economic downturn led to an increase in the overall number of day users at domestic violence shelters in areas affected by the downturn, but not necessarily had an impact on the number of new day users. Thus, we believe that the increase in the number of day users is mainly driven by domestic violence victims who already live with a violent partner, and that the violence has become more frequent.

Our findings support the theory of exposure reduction, particularly due to the nature of the work of many people in the oil industry. When workers on oil platforms lose their job, they spend considerably more time at home with their spouse. If these newly unemployed workers inhibit violent tendencies, their spouses become more exposed to their violent behaviour, explaining the increase in the number of day users. This also implies that increased unemployment is one of the key drivers of domestic violence in our case.

In the presented literature, the household bargaining model is seen as an important theoretical foundation for explaining domestic violence. The model predicts that an increase in the overall unemployment rate will have no effect on domestic violence, but that an increase in male unemployment will reduce domestic violence. In the counties that were hardest hit by the regional economic downturn, the male unemployment rose sharply but the development of female unemployment differed between the counties, as can be seen in section (A.5) in the appendix. For instance, in Rogaland, the female unemployment rate rose between 2013 and 2016. The model of household bargaining would thus likely predict no effect on the levels of domestic violence in Rogaland. In Møre og Romsdal and Vest-Agder, the female unemployment rate initially rose following the oil price decline, but was stable from the end of 2014. According to the household bargaining model, we should have seen a decline in the levels of domestic violence as mainly the male unemployment rate increased in these counties. Because the development of the ratio between the male and the female unemployment rate both differs over time for each county and between counties, the overall prediction of the model is unclear. However, it is evident that the household bargaining model would not predict an increase in the levels of domestic violence.

It might be that the economic downturn both prevented and provoked incidents of domestic violence. However, we will not be able to distinguish between these two effects as we only observe the overall level of violence. Our findings are therefore not necessarily inconsistent with the household bargaining model, because the effect predicted by the theory of exposure reduction could have been stronger than the effect predicted by the household bargaining model.

Our baseline estimates suggests that the number of residents at domestic violence shelters increased as a consequence of the regional economic downturn. The significance of these estimates are however highly dependent on the model specification, and so we are careful to conclude that the regional economic downturn caused an increase in the number of residents. We find two possible explanations for this: Firstly, a weakness with the data on residents is that the capacity of domestic violence shelters for taking in residents is limited (Bufdir, 2015a). Domestic violence shelters are not allowed to refuse to help victims, but they can refer them to a different shelter (Bufdir, 2015a). Because shelters could operate at maximum capacity with regards to residents, the variation in the data do not necessarily reflect the actual amount of victims who sought help at a specific shelter. Secondly, we know that characteristics of residents are somewhat different from characteristics of day users. For example, a higher proportion of day users compared to residents have a full time job, while a higher proportion of residents than day users have immigrant background, see plots in section (A.1). Furthermore, in conversation with Bufdir, they suggested that day users are more likely to have a spouse working in the oil industry compared to residents. This could explain why the oil price shock only had a small or insignificant effect on the number of residents at domestic violence shelters.

7.2 Assessment of the Validity of Shelter Users as a Measure of Domestic Violence

The number of users of domestic violence shelters do not capture all incidents of domestic violence, and we might measure only a particular type of violence. It is plausible that we capture the more severe incidents as the majority of the shelter users had been in contact with some other aid agency, such as a casualty clinic or the police, prior to their shelter visit (Bufdir, 2017a).

An increase in the number of users of domestic violence shelters do not necessarily represent an increase in the levels of domestic violence. This threatens the validity of shelter users as a measure of domestic violence. For instance, the frequency of follow-ups of users could partly be determined by a shelter's level of resources. A change in the level of resources could then lead to a change in the level of registered users without there being a change in the levels of domestic violence. Another potential source of error is that shelters might have become better or worse at providing the public with information about their services or at registering users. We have therefore gone through some of the shelters annual reports to investigate the validity of the number of shelter users as a measure of domestic violence. We excluded Hedmark and Troms from our analysis based on the aforementioned issues, see section (5.2). However, we found nothing in the annual reports indicating that the number of shelter users is a bad measure of domestic violence for the counties we have included in our analysis.

7.3 Dependency Problems

Because we have panel data on county level, our data is susceptible to serial correlation and intra-county correlation. Intra-county correlation would in our case mean that there exist dependencies between users of shelter services within the same county. It is plausible that such dependencies exist as people in the same county share the same neighborhood and background characteristics. Serial correlation means that the outcome in one period is correlated with previous outcomes. Serial correlation is present if for instance the number of shelter users is high for several consecutive years. If such dependencies exist in our data and they are not adjusted for, our standard errors would likely be underestimated.

Clustering the data on county level would allow for the previously mentioned dependencies in our data. A limitation to our data set is however that our sample is small and contain few groups, making it problematic to cluster the standard errors. Clustering is also not possible due to the structure of our data, as we use aggregated data at county level. Had we used data at shelter level, it would be possible to cluster at county level, but there would still be too few clusters and we would underestimate the dependencies in our data (Angrist and Pischke, 2008).

7.4 Limitations to the Estimation Method

7.4.1 The Parallel Trends Assumption

The premise for identification using a DiD strategy is the assumption of parallel trends. The estimates can only be given a causal interpretation if one believes that in absence of the treatment, the development of the treatment group would be the same as for the control group. For both day users and residents, the trends seem fairly parallel even when we experiment with different control groups as can be seen in section (A.2) and (A.4) in the appendix. However, visual inspection is no formal test for whether the parallel trends assumption holds, and the treatment and the control group might have developed differently even in absence of the treatment. As an additional check we have looked at how the treatment group and the control group develop on several observable characteristics, depicted in table (5.1). The summary statistics give no indication of violation of the parallel trends assumption as the observable characteristics develop similarly for the control group and the treatment group.

The trends of the new day users plotted in section (A.3) seem to violate the parallel trends assumption. Thus, the premise for identification using a DiD strategy is not fulfilled, and the estimates presented should not be given a causal interpretation. It could be that we do not find parallel pre-treatment trends for the data on new day users because there are quite few new day users compared to the overall level of day users and residents. Since the pre-treatment mean of the control group is approximately 3 day users per 100,000 people each quarter, there will likely be considerable random variation in the number of new day users.

7.4.2 The Oil Price Shock is Not a Clear Cutoff

A limitation with our set-up is that our treatment, the oil price shock, does not represent a clear cutoff. The DiD setup is typically used to assess consequences of policy changes, where the policy is implemented at a specific date. Although the oil price started to decline mid-2014, people and firms might have thought of the price fall as temporary in the beginning. Furthermore, the consequences of the oil price shock was not seen immediately after the price started to decline, as it takes time for firms to adapt. However, an article from Vest24 states that the oil price decline affected the unemployment levels already in October 2014 (Havre, 2014). This indicates that although our cutoff is not as clear as for a typical policy change, it is still usable for our purpose.

7.4.3 All Counties are Treated

The Norwegian economy is highly dependent on oil, and people in all Norwegian counties work in direct oil related industries. Although some counties only have a small share of their workers employed in oil related industries, one can argue that to some extent all counties were affected by the oil price shock. Thus, the counties in the control group were also partly treated. Because the control group was partly treated, we might have underestimated the effect of the regional economic downturn on domestic violence.

7.4.4 Composition Change

One possible threat to identification is that the regional economic downturn could have motivated people to move from counties in the treatment group to counties in the control group. To investigate this, we have looked at migration flows, see table (7.1). From 2014 to 2015 we find a 40 percent increase in net migration from the treatment group to the control group, but the absolute number of net movers make up a small share of the total population in the control group. Furthermore, according to Johannes Sørbø, senior advisor and labour market expert at NAV, analyses of the period 2013 to 2017 show that it was unusual to move in order to find a job (Sørbø, 2018). We therefore assess the potential impact of migration on our analysis as being minimal.

Table 7.1: Net Migration from the Treatment Group to the Control Group (Number of people)

	2012	2013	2014	2015	2016
Migration from Treatment Group to Control Group	4369	4315	4439	4902	5226
Migration from Control Group to Treatment Group	3705	3796	3649	3584	3484
Net Migration from Treatment Group to Control Group	**664**	**519**	**790**	**1318**	**1742**

Source: SSB, 2018c

8 Conclusion

Our thesis adds to the small, but growing economic literature exploring the causes of domestic violence. We find that the regional economic downturn following the oil price shock in 2014 increased the number of day users at domestic violence shelters. Specifically, we find that the downturn increased the number of day users in Rogaland, Møre og Romsdal and Vest-Agder by 9.97 day users per 100,000 people each quarter. This translates to an increase of 26 percent from the mean number of day users prior to the regional economic downturn. The findings are robust, and do not change considerably with different model specifications. This gives credibility to our research design.

It is more difficult to conclude on the effect of the regional economic downturn on the number of residents. Different model specifications suggest that the effect of the downturn is either small or insignificant. Our baseline results suggest that the number of residents increased by 1.7 residents per 100,000 people each quarter in oil intense counties. This equals a 13 percent increase from the mean number of residents prior to the regional economic downturn. Furthermore, we find no significant effect of the downturn on the number of new day users.

We present suggesting evidence that the effect of the economic downturn on the levels of domestic violence manifests through increased unemployment. Unemployment is often correlated with other factors that affect domestic violence, and domestic violence could in itself increase unemployment. This creates challenges for researchers who seek to examine the effect of unemployment on the levels of violence. However, we overcome the issue of endogeneity by using an exogenous shock to unemployment, and our paper contributes to the economic literature on domestic violence by documenting a causal effect of an economic downturn on the levels of violence.

Our results suggest that domestic violence shelters should prepare for a greater influx of people during economic downturns. As a consequence, the shelters' need for resources will increase during downturns and ideally we should have a flexible system that grant more resources to shelters in times of crises.

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A | Appendix

A.1 Descriptive Statistics

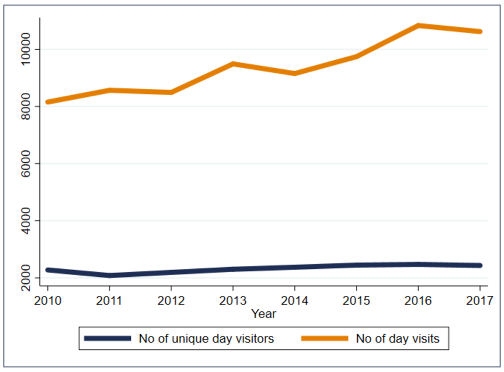

Figure A.1: Number of day users and total no of day visits in the period 2010-2017

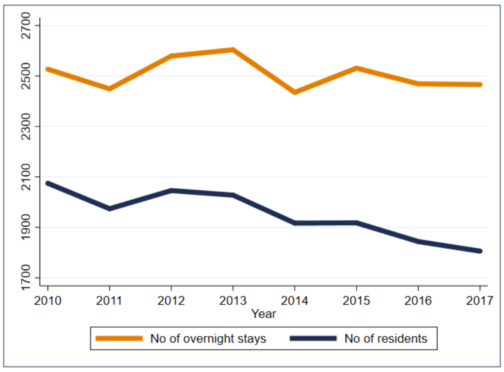

Figure A.2: Number of residents and overnight stays in the period 2010-2017

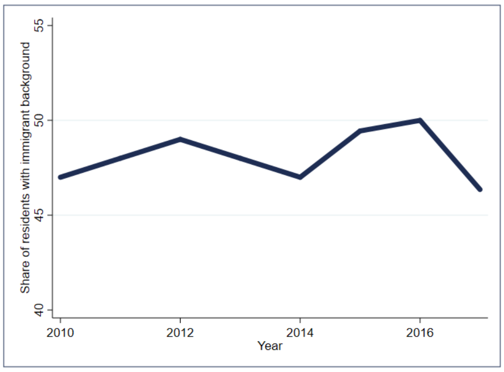

Figure A.3: Share of day users with immigrant background in the period 2010-2016 (percent)

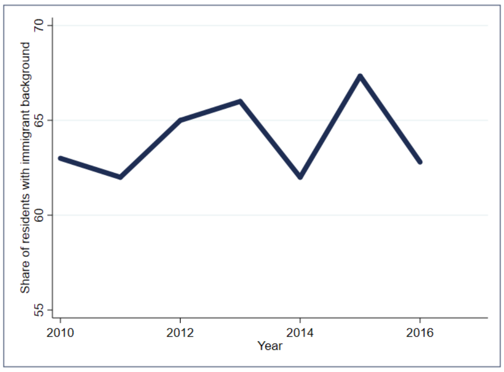

Figure A.4: Share of residents with immigrant background in the period 2010-2016 (percent)

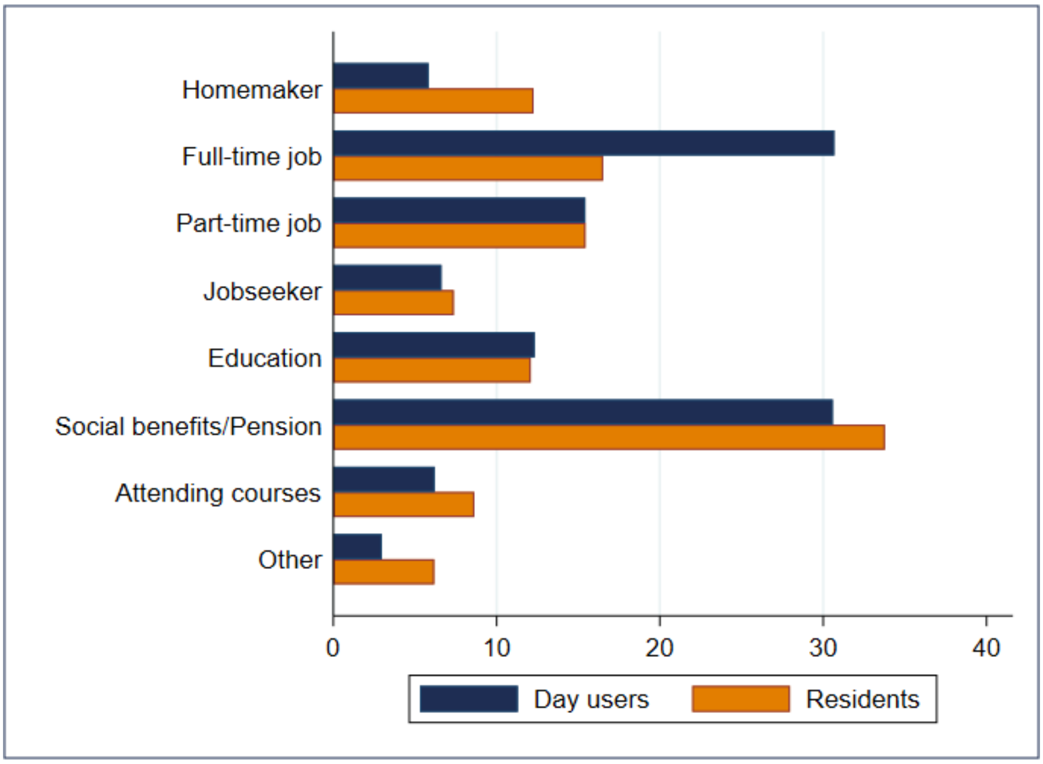

Figure A.5: Work status of day users and residents in 2017 (percent)

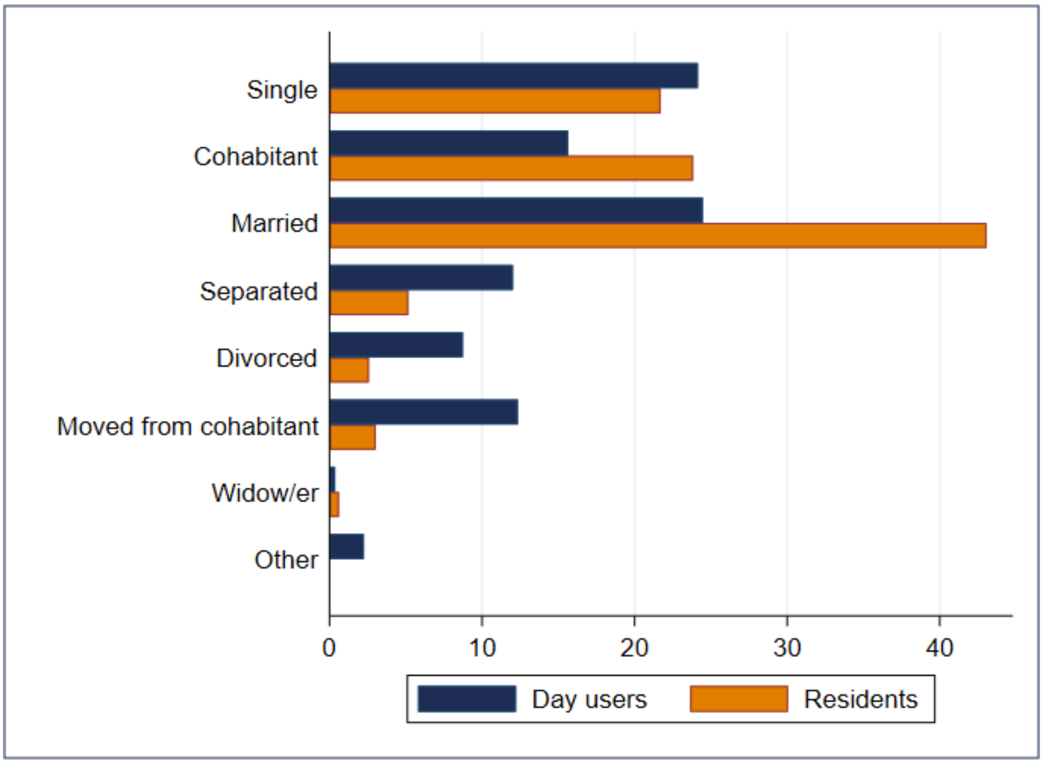

Figure A.6: Relationship status of day users and residents in 2017 (percent)

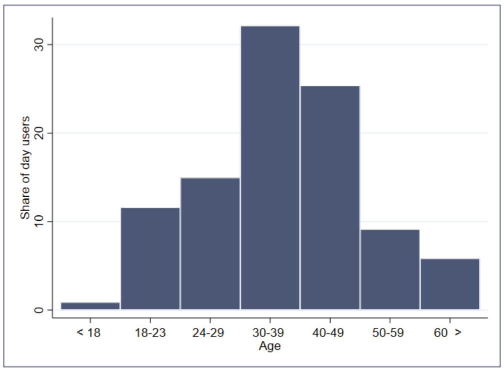

Figure A.7: Day users age at first visit - 2017 (percent)

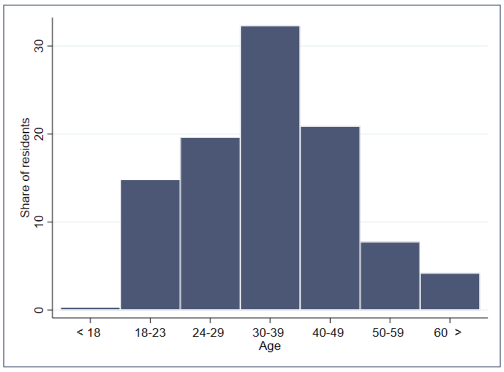

Figure A.8: Resident age at first visit - 2017 (percent)

A.2 Trend Plots Day Users

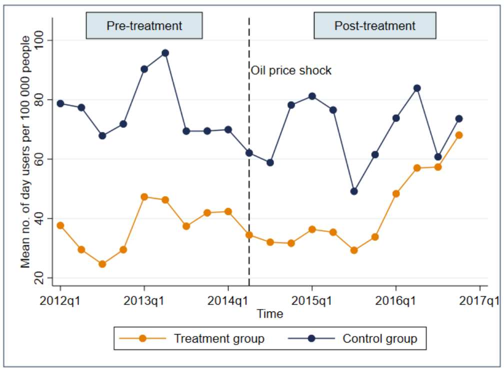

Figure A.9: Full Sample

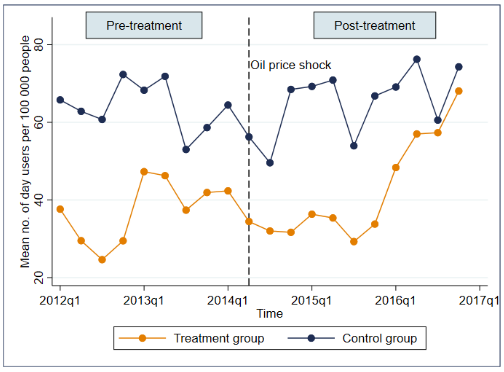

Figure A.10: Oslo excluded

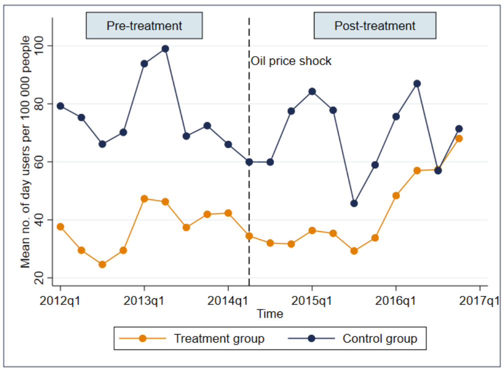

Figure A.11: Nordland excluded

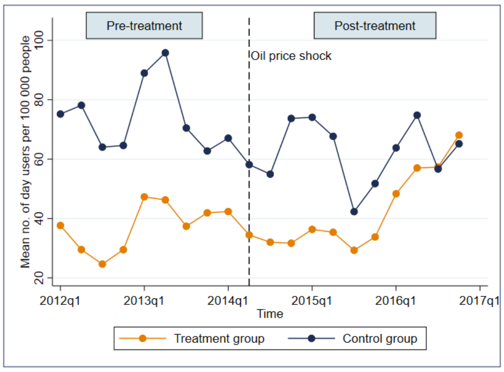

Figure A.12: Østfold excluded

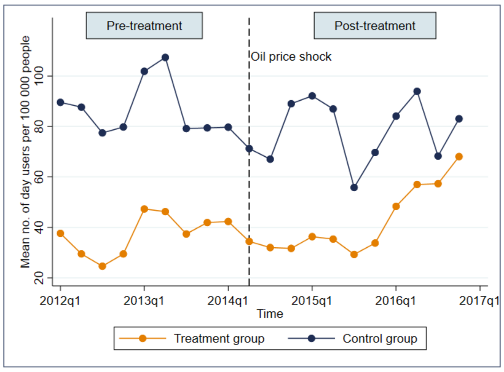

Figure A.13: Oppland excluded

A.3 Trend Plots New Day Users

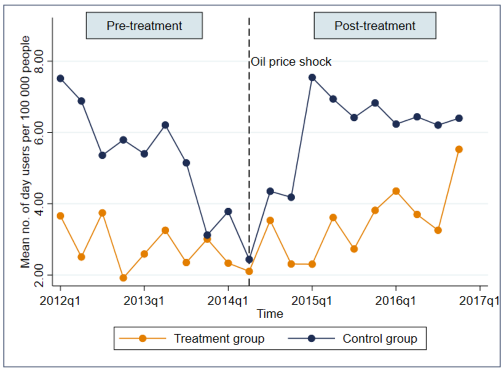

Figure A.14: Full Sample

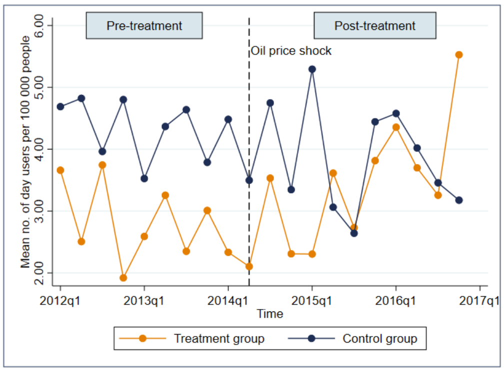

Figure A.15: Oslo excluded

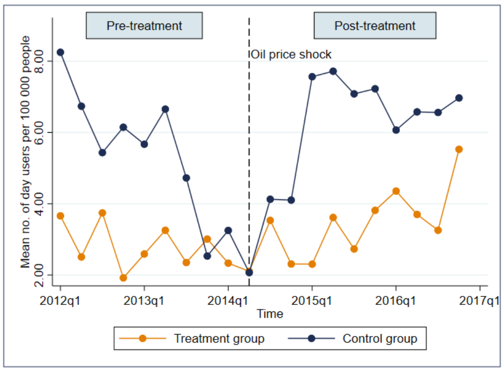

Figure A.16: Nordland excluded

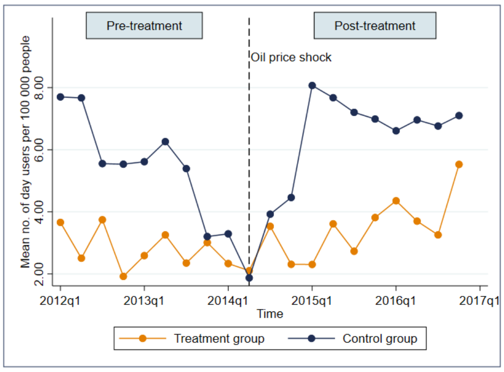

Figure A.17: Østfold excluded

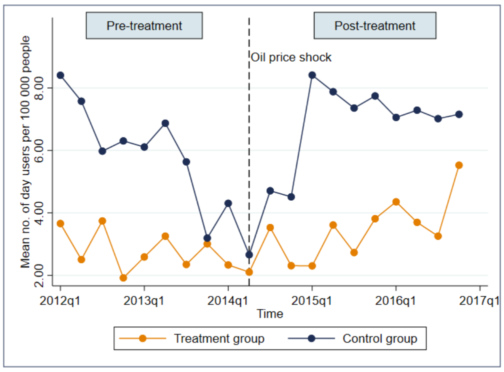

Figure A.18: Oppland excluded

A.4 Trend Plots Residents

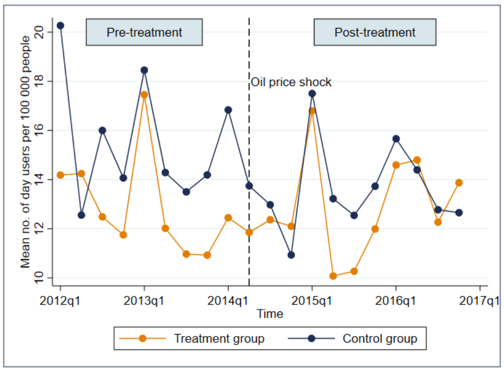

Figure A.19: Full Sample

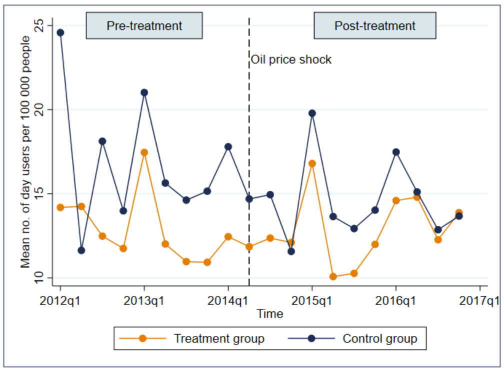

Figure A.20: Oslo excluded

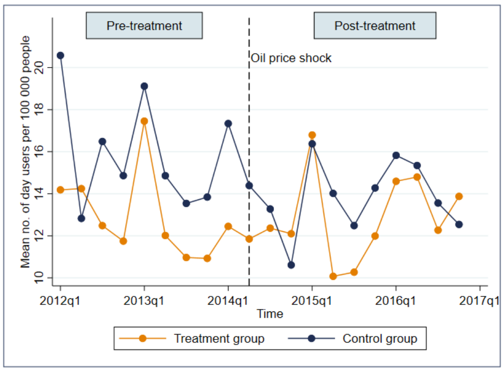

Figure A.21: Nordland excluded

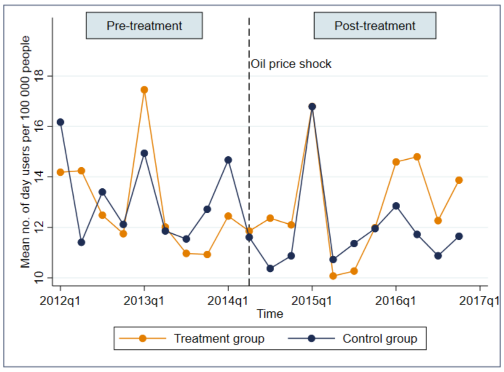

Figure A.22: Østfold excluded

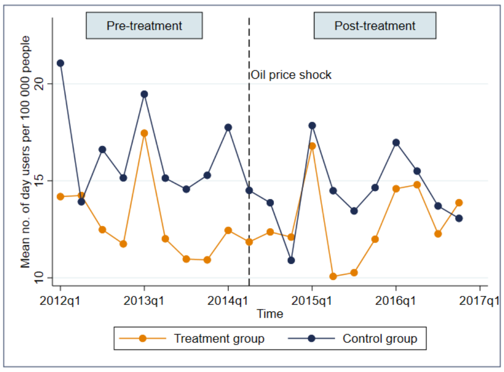

Figure A.23: Oppland excluded

A.5 Unemployment Rate - Treatment Group

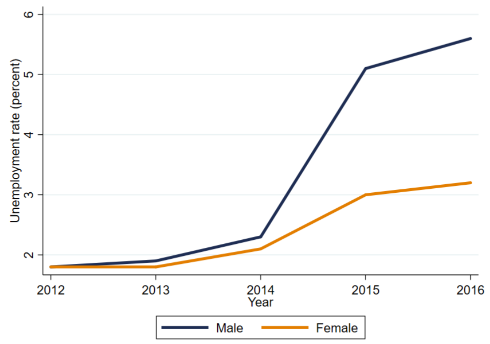

Figure A.24: Gender Specific Unemployment Rates - Rogaland

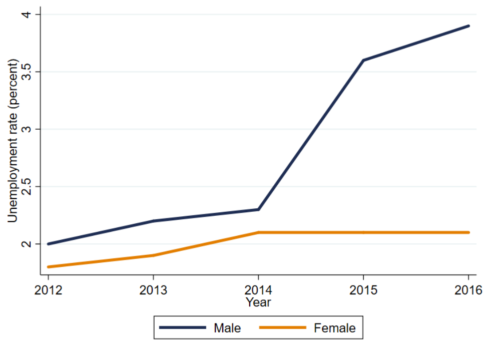

Figure A.25: Gender Specific Unemployment Rates - Møre og Romsdal

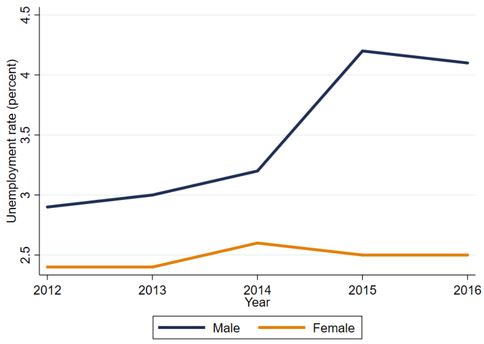

Figure A.26: Gender Specific Unemployment Rates - Vest-Agder

County	Share of employees (%) Direct oil related industries	Share of employees (%) Direct and indirect oil related industries
Rogaland	25.2	40
Møre og Romsdal	13.3	21
Hordaland	13.2	21
Vest-Agder	10.7	17
Aust-Agder	6.3	10
Nord-Trøndelag	5.1	8
Buskerud	5.0	8
Sogn og Fjordane	5.0	8
Akershus	5.0	13
Telemark	4.4	7
Vestfold	3.8	6
Sør-Trøndelag	3.8	6
Finnmark	3.0	5
Oslo	2.0	9
Troms	2.0	3
Nordland	1.8	3
Østfold	1.2	2
Hedmark	0.7	1
Oppland	0.6	1

Table A.1: Share of Employees in Oil Related Industries. Source: Blomgren et al., 2015

A.6 Robustness Tests

A.6.1 Removing One County at a Time

Table A.2: Effect of oil price shock on the number of day users at domestic violence shelters - Without Rogaland, without dummy controls

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Baseline Results	(5) Including population weights
Day Users	41.55				
Treated x Post		13.13***	18.16***		
		(4.238)	(5.089)		
Exposure				117.9***	163.9***
				(38.33)	(45.75)
Observations	20	120	120	120	120
Adjusted R^2		0.853	0.808	0.853	0.808
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of day users per 100,000 inhabitants. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the baseline results from equation (5.3). Column (5) shows the estimates when running equation (5.3) with WLS.

Table A.3: Effect of oil price shock on the number of day users at domestic violence shelters - Without Møre og Romsdal, without dummy controls

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Baseline Results	(5) Including population weights
Day Users	30.71				
Treated x Post		7.398*	10.42**		
		(3.757)	(4.631)		
Exposure				27.12	40.99*
				(19.84)	(22.26)
Observations	20	120	120	120	120
Adjusted R^2		0.877	0.851	0.875	0.849
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of day users per 100,000 inhabitants. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the baseline results from equation (5.3). Column (5) shows the estimates when running equation (5.3) with WLS.

Table A.4: Effect of oil price shock on the number of day users at domestic violence shelters - Without Vest Agder, without dummy controls

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Baseline Results	(5) Including population weights
Day Users	41.63				
Treated x Post		10.84**	13.13***		
		(4.373)	(4.744)		
Exposure				38.47*	48.81**
				(20.54)	(22.41)
Observations	20	120	120	120	120
Adjusted R^2		0.854	0.829	0.849	0.824
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of day users per 100,000 inhabitants. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the baseline results from equation (5.3). Column (5) shows the estimates when running equation (5.3) with WLS.

Table A.5: Effect of oil price shock on the number of residents at domestic violence shelters - Without Rogaland, without dummy controls

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Baseline Results	(5) Including population weights
Residents	13.14				
Treated x Post		1.575	1.610		
		(1.042)	(1.012)		
Exposure				15.53	15.35*
				(9.362)	(9.141)
Observations	20	120	120	120	120
Adjusted R^2		0.720	0.720	0.721	0.720
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of residents per 100,000 inhabitants. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the baseline results from equation (5.3). Column (5) shows the estimates when running equation (5.3) with WLS.

Table A.6: Effect of oil price shock on the number of residents at domestic violence shelters - Without Møre og Romsdal, without dummy controls

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Baseline Results	(5) Including population weights
Residents	13.75				
Treated x Post		1.161	1.347		
		(0.972)	(0.888)		
Exposure				7.242	6.942
				(4.713)	(4.197)
Observations	20	120	120	120	120
Adjusted R^2		0.725	0.713	0.726	0.714
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of residents per 100,000 inhabitants. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the baseline results from equation (5.3). Column (5) shows the estimates when running equation (5.3) with WLS.

Table A.7: Effect of oil price shock on the number of residents at domestic violence shelters - Without Vest Agder, without dummy controls

	(1) Mean Pre-treatment	(2) Baseline Results	(3) Including population weights	(4) Baseline Results	(5) Including population weights
Residents	12.21				
Treated x Post		2.299**	2.058**		
		(0.912)	(0.824)		
Exposure				10.50**	8.858**
				(4.484)	(4.003)
Observations	20	120	120	120	120
Adjusted R^2		0.731	0.718	0.728	0.715
Fixed Effects		Yes	Yes	Yes	Yes
County Weights		No	Yes	No	Yes
Control Variables		No	No	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of residents per 100,000 inhabitants. Column (1) shows the mean outcome values in the period 2012Q1 to 2014Q2 for the counties that were hardest hit by the regional economic downturn. Column (2) shows the baseline results from equation (5.2). Column (3) shows the estimates when running equation (5.2) with WLS. Column (4) shows the baseline results from equation (5.3). Column (5) shows the estimates when running equation (5.3) with WLS.

A.6.2 Using Observations at Shelter Level

Table A.8: Effect of oil price shock on the number of day users at domestic violence shelters - Using observations at shelter level

	(1) Baseline Results	(2) Including population weights	(3) Baseline Results	(4) Including population weights
Treated x Post	11.01^{*}	13.39^{***}		
	(5.784)	(4.552)		
Exposure			40.34	53.01^{**}
			(27.68)	(25.35)
Observations	400	400	400	400
Adjusted R^2	0.777	0.806	0.776	0.804
Fixed Effects	Yes	Yes	Yes	Yes
County Weights	No	Yes	No	Yes
Control Variables	No	No	No	No

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The outcome variable is the quarterly number of day users per 100,000 inhabitants. Column (1) shows the baseline results from equation (5.2). Column (2) shows the estimates when running equation (5.2) with WLS. Column (3) shows the baseline results from equation (5.3). Column (4) shows the estimates when running equation (5.3) with WLS.