Independent aging: Evaluation of the adoption of welfare technologies in Lister

Thesis submitted as a part of the Master of Philosophy Degree in Health Economics, Policy and Management

Eduardo Alberto Ramírez Lizardi

Supervisor: Henning Øien

University of Oslo, Faculty of Medicine, Department of Health Management and Health Economics

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Abstract

This thesis evaluates the implementation of a welfare technology program in 6 Norwegian municipalities. The program's objective is to promote independence in older populations and reduce the need for institutional services. I estimate the effects of the program by using an augmented synthetic control method (ASCM). My results show no evidence that the program had an effect on long term care expenditures, mortality, and the utilization of specialized and municipal health services. This thesis, together with previous literature highlights the complexities behind the evaluation of these type of technologies and provides suggestions for further research.

Contents

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To Pia for her company in the library days,

To my family,

1 Introduction

Despite its potential to provide independence, reduce nursing costs, and improve quality of life, the evidence on the effects of welfare technologies remains inconclusive. As the population grows older, the demand for long term care (LTC) services increases. This increase is explained in part by the growing prevalence of chronic diseases and increased frailty among older populations (Barlow, Singh, Bayer, & Curry, 2007). This issue is relevant in regions where access to care is limited by geographical barriers or where resources are not enough to meet the growing population's demands (Miller, 2007).

In Norway, where the LTC is publicly provided and funded by taxes, health expenditures represented around 11.3 % of the Gross Domestic Product (GDP) in 2021 (OECD, 2021). LTC expenditures are higher in Norway than in any other member of the European Union. Norwegian LTC expenditures correspond to around 25.9% of all health expenditures (Sperre et al., 2019). Following current demographic trends, Norway is expected to experience a demographic shift where older populations will represent around 30% of the population by 2070 (Syse, Thomas, & Gleditsch, 2020). These changes could represent a higher burden to the provision of LTC and to the welfare state. Overcoming these challenges will require new approaches in the provision and organization of care services.

Recent policy developments have used welfare technologies as a tool to continue to provide care to patients that need continuous care and follow-up. By doing this, welfare technologies aim to address two main issues: First, they intend to increase the quality of care by providing higher responsiveness and monitoring. The second issue they address is cost containment. When implemented properly, welfare technology has the potential to reduce travel costs, nursing expenses, and the need for institutional spaces (Bjørkheim et al., 2016).

In this thesis, I evaluate a welfare technology program in the Norwegian region of Lister. I use the introduction of the program in 2014 to analyze its effects on the levels of expenditures, utilization of municipal services, number of hospital admissions, and measures of mortality. I evaluate the program using an augmented synthetic control method (ASCM), a variation of the initial framework by Abadie & Gardeazabal (2003) that allows intervention in multiple units (Ben-Michael, Feller, & Rothstein, 2019).

The program is part of the National Welfare Technology Program (NWTP) and its goal is to reduce the need for nursing home (NH) spaces and home-based care (HBC) services (Helsedirektoratet, 2012; Røhne, Svagård, & Holmesland, 2016). In Lister, the program emphasizes the use of security packages. These devices consist of self-triggering sensors, detectors, and alarms (Ministry of Health and Care Services, 2009). Considering the relevance of the program and its objective, this thesis aims to answer whether or not the program had any effect on three groups of variables. The first group relates to the use of LTC resources, represented by the level of expenditures on LTC services. These include the expenditures on NH and HBC services. The second group relates to the utilization of municipal health services and the demand for specialized health services. These measures include the use of NH spaces, users in NH, users of HBC, and hospital admissions. Finally, the third dimension relates to measures of mortality per 1000 inhabitants and age-specific deaths.

This thesis contributes to the literature on the use of welfare technologies by producing a quantitative evaluation through a causal identification strategy. In contrast to the existing literature on welfare technologies, this project evaluates the effectiveness of the program at an aggregate level. It also contributes by exploring the effects of these technologies on other variables such as mortality and hospital admissions, often not included in the previous literature. Health outcomes are relevant to analyze since they are not under the direct control of the institution implementing the program. My results also contribute by providing potential areas of improvement for further research in this area.

In this thesis, I found that the introduction of welfare technology based on security packages in the region of Lister showed no evidence of a significant effect on any of the dimensions of interest. However, I recognize that the research is limited by multiple factors that could bias the results. Limitations of this research relate to the aggregation of units where only a few individuals were treated, computational limitations in the selection of covariates, and potential violations of critical assumptions such as no externalities and homogeneous treatment.

The rest of this thesis is organized as follows. Section 2 provides an overview of policy developments around welfare technologies and LTC. Section 2 also provides a description of the institutional background of LTC in Norway and the development of the National program of welfare technology. In section 3, I present a description of the data and the methods employed to evaluate the program. Sections 4 and 5 present the results of the study and section 6 concludes.

2 Background

2.1 Trends in long term Care Services

Fundamentally, long term care (LTC) refers to the care of chronic illness and disability within a range of formal and informal institutions (Norton, 2000). This definition includes care services to people who need assistance in daily activities such as bathing, eating, and dressing (Pestieau, Cremer, & Ponthière, 2012). The OCDE (2021) defines LTC facilities as those nursing homes and residential facilities that provide specially designed infrastructure to the attention of people with moderate or severe functional restrictions. This wide definition includes within its scope patients of different age groups, diagnostics, and characteristics (OECD, 2021). In Norway, for instance, municipal services provide LTC services through nursing homes, sheltered housing provided by the municipality, and patients' homes (Sperre, et. al, 2020).

Projections of health expenditure in OECD countries as a percentage of their GDP anticipate an increase of 1.4% from 2018 to 2030. In Norway, health expenditures are expected to increase by 2% over the same period. (Lorenzoni, Marino, Morgan, & James, 2019; OECD, 2019). Changes in epidemiological needs, demography, rising income, and the adoption of new technologies are key drivers of the rise in health expenditures (Ke, Saksena, & Holly, 2011).

As a higher proportion of the population lives beyond the age of 80, the number of persons needing LTC services increases; then, meeting patients' demands requires an expansion of social and welfare services (Breyer, Costa-Font, & Felder, 2010). In 2018, LTC expenses represented 1.5% of the OECD GDP (OECD, 2020). The report shows a wide variation in how LTC services are provided, organized, and funded. For instance, The Nederlands and the Scandinavian countries show the highest levels of LTC expenditures in the OECD. In 2018, these countries spent on average 3.5% of their GDP. Around 92-94% of these services are publicly funded. In terms of coverage, these countries' LTC policies focus on the provision of nursing home services and home-based-care services (Ringard et al., 2013)

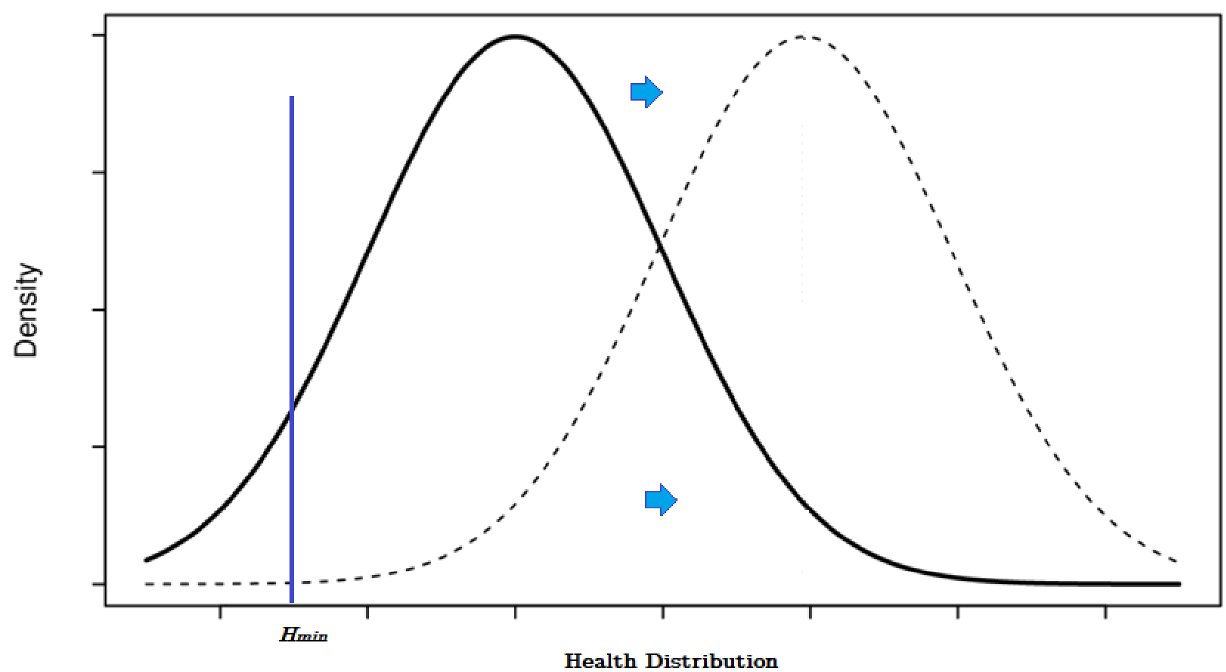
Thus, policies that focus on costs containment are relevant for the provision of LTC services. in OECD countries, the share of the population aged over 65 years is expected to grow by 9.4% from 2017 to 2050, while the share of the population aged over 80 years is likely to more than double by 2050 (OECD, 2019). In Norway, aging shows a similar trend to the OECD; the share of the population above 65 years is expected to raise by 12% by 2060 (Syse, Thomas, & Gleditsch, 2020) These changes could represent a burden on the welfare state due to higher demand for pensions, welfare programs, reduced labor supply, and increased demand for nursing services.

According to Norton (2000), the demand for LTC services is dependent on two factors: health status and the out-of-pocket price of close substitutes (i.e. informal care). Similarly, Siciliani (2013) argues that decisions over the use of LTC and other services are often determined simultaneously and respond to other unobserved variables such as personal preferences and familiar circumstances. In the same way, substitution and complementarity between different types of care depend on whether these services are substitutes or complements in the production of health (Øien, 2016), which one could argue depend on the levels of skills (Siciliani, 2013) or technology required to produce them.

To test the hypothesis of whether medical innovation has an impact on the use of formal LTC services or not, Lichtenberg (2009), estimates the impact of pharmaceutical and medical procedure innovations on the use of nursing home services. The author finds a reduction of about three quarters in the use of NH services that is associated with pharmaceutical innovation between 1985 and 1999. The author explains these results by using a simple model where the demand for formal LTC services starts after health status H drops below a given level $Hmin$ (See figure 1). In this model, the proportion of people demanding LTC services is the number of individuals on the left of Hmin. The introduction of innovations that raise the overall level of health would then produce a shift in the distribution, reducing the number of people demanding formal LTC. However, authors such as Consoli, McMeekin, Stan, Metcalfe, & Ramlogan (2009) argue that since innovation is a learning process that involves uncertainty around new processes and their outcomes, the expected benefits of new technologies or treatments are not usually clear in the short term.

Recently, LTC policies have focused on a wide number of country-specific transformations that respond to these epidemiological, technological, and demographic changes (Blank, Burau, & Kuhlmann, 2017). In many countries, policy developments start to recognize the importance of LTC as a basic need of citizens and a social right. Similarly, LTC policies have undergone a wide range of transformations aimed at containing costs and increasing coverage (Pavolini & Ranci, 2013).

Figure 1: A hypothetical shift in the health distribution[a]



[a]Source: Lichtenberg (2009)

2.2 Long Term Care Services in Norway

In the Norwegian health care system, primary care and LTC services are provided and financed at the municipal level (Sperre et. al, 2020). The Norwegian health care system is characterized by the public provision of care, which is predominantly funded by taxes through a semi-decentralized structure that pursues equity (Magnussen, Vrangbæk, Saltman, & Martinussen, 2009).

With around 25.9% of all health expenditures, Norway spends more than any member of the European Union on LTC services (Sperre et. al, 2020). In Norway, the provision of LTC services is a responsibility of the municipalities. In addition to the provision of LTC through NH services and HBC services, the municipalities determine the type of service and the amount of care that patients receive (Borge, 2013).

Authors such as Blank, Burau, & Kuhlmann (2017) and Pavolini & Ranci (2013) argue that the provision of LTC regimes responds to two components. First, changes in demographic composition and prolonged life expectancy (Breyer, Costa-Font, & Felder, 2010) and social preferences towards the provision of informal care services embody the differences between the responsibilities of the State and families. In this regard, the Scandinavian model, and specifically the Norwegian model, which emphasizes the role of the State in the provision of LTC services seems to result in a lower burden to families and especially to middle-aged females that otherwise would provide informal care to the frail and elderly (Karlsson, Iversen, & Øien, 2012).

2.2.1 Home Based Care services

In this thesis, I consider the services that are specific to the Norwegian Context, namely, home-based care, care institutions, and homes for care purposes. Specifically, I use the definitions provided by Statistics Norway (2021). Accordingly, HBC includes all the activities related to home help and home nursing. According to Holm et al. (2017), home nursing is delivered by registered nurses who provide services that include rehabilitative, therapeutic, and assistive activities in addition to nursing.

2.2.2 Care institutions

Care institutions are buildings of full-time services, where areas of the infrastructure and household are shared by the residents. This definition includes nursing homes, and old peoples' homes (Statistics Norway, 2021). These institutions are designed for patients that need additional care and help with daily activities, these normally include the frail and elderly (Sperre, et al. 2020). The provision of these services is conditioned on the users' needs and it is determined by municipal assessment (Helsenorge, 2019).

2.2.3 Homes for care purposes

In Norway, homes for care purposes provide care services to the elderly, disabled, and people with mental illness (Statistics Norway, 2021). As mentioned in Ringard et al. (2013), the division between homes for care purposes and other institutions is often hard to distinguish since they offer similar services to nursing homes. Care homes can be owned by the municipalities, the users, or housing associations (Helsenorge, 2019).

2.3 Technologies in Long Term care services

Technology is argued to be key in reducing the burden of an ageing population on health care systems. Health technologies often introduce improvements in quality, efficiency, and treatment costs at the expense of higher prices and increased complexity (Christensen et al., 2017). Recent developments emphasize the role of health information technologies (HIT) in improving the responsiveness of health services and the access to care. HIT are devices that store, retrieve, share, and use health information for communication and decision-making (Stefanacci & Cantelmo, 2009). Chaudhry et al. (2006) note that the use of HIT capabilities such as documentation, result management, decision support, storage, and communication is often associated with increases in efficiency, and quality, and with uncertain effects on costs. In general, the literature on HIT summarizes the improvements from health technologies to reductions in information costs and enhanced decision support (Agha, 2014; Young, Willis, Cameron, & Geana, 2014).

In this thesis, I will focus on the use of a particular type of technology within HIT. I am interested in exploring the use of welfare technologies and their effect on health and expenditures. In the literature, the term telecare is used interchangeably with telehealth, telemedicine, and in some countries welfare technology. The term refers to the use of communication technologies to provide direct care to patients with the objective to support independence and welfare (Barlow, Singh, Bayer, & Curry, 2007; Sintonen & Immonen, 2013). In geographically remote communities where the supply of health care services is limited, users may benefit from having access to care that otherwise would not be available, in addition to enhanced responsiveness of local health services (Miller, 2007). In Norway, these technologies have been adopted under the name of welfare technology, which Helsedirektoratet (2012) defines as user-oriented technologies aimed to support and enforce safety, mobility, and independence while ensuring better use of resources related to the provision of other welfare services.

In this regard, welfare technologies have the potential to provide independence and improve quality of life. By providing real-time information, practitioners can detect emergencies and anticipate the type of response a patient needs. Therefore, these technologies have the potential to reduce the use of emergency services and prevent patients from developing severe symptoms. Nevertheless, to redesign and move care from the clinical practice to patients' homes, welfare technologies require new dependencies (i.e trained staff), infrastructure, and knowledge which may explain their slow uptake and the mixed results around the effectiveness of their adoption (Turner & McGee-Lennon, 2013).

As the population grows older and the burden of non-communicable diseases rises, welfare technologies are the usual choice of policymakers to provide care to the elderly and the chronically ill. While doing this, welfare technologies can help to control costs and to reduce the burden on the hospital system (Barlow, Singh, Bayer, & Curry, 2007). Because of these demographic and epidemiological changes, welfare technologies have been targeted to populations of patients that require continuous follow-up from nursing and specialist services.

One limitation of the evaluation of welfare technologies as a whole is the heterogeneity of patient populations and the wide range of technologies adopted in these projects (Olivari et al., 2018). Some of these technologies include complex monitoring systems for a wide diversity of health indicators that cover diseases such as chronic pulmonary obstructive disease (COPD), diabetes, and heart disease (Helsedirektoratet, 2012). As a result, the literature provides mixed results in terms of effectiveness in costs and health outcomes. These outcomes vary depending on the type of disease and the type of technology included in the package.

Notwithstanding the lack of evidence around the effectiveness of welfare technologies, countries like the UK, Denmark, Japan, and the United States have deployed welfare programs. These projects emphasize the importance of evaluating their sustainability as a support to the aging population (Turner & McGee-Lennon, 2013). Evidence from RCTs shows that the use of welfare technology has had mixed results in both health and economic outcomes. In a randomized controlled trial, that included 1225 participants from Northern Denmark municipalities, Udsen, et al. (2017) found that the use of welfare technologies to treat patients with COPD, did not provide significant benefits in terms of Cost-efficiency or gains in Quality Adjusted Life Years (QALYs). Similarly, an RCT (n = 945) performed by Howard et al. (2021), to determine whether telecare improved time living independently for individuals living with dementia resulted in non statistically significant improvements in the variable of interest and showed a reduction in QALYs for those in the treatment arm.

2.4 National program of welfare technology (*Nasjonalt velferdsteknologiprogram*)

According to Ministry of Health and Care Services (2011), the Norwegian health care system faces three main challenges on the delivery of care: a shortage in volunteer services, lack of coordination, and coverage of psycho-social needs. The report highlights that municipal services are particularly challenged in the management of falls, loneliness, and cognitive decline. To address this problem, the whitepaper on the future of care (2012-2013) by Ministry of Health and Care Services (2013a), announced the creation of the national welfare technology program (NWTP), which consists of 6 measures: Standardization of welfare technologies, development and testing in municipalities, knowledge production, development of good models of implementation, competence building, and the creation of a legal framework.

Since 2011, with guidance from the Norwegian Directorate of Health, the Directorate for E-Health, and the Association of Local & Regional Authorities, different Norwegian municipalities started to implement welfare technologies as part of the NWTP (Breivik, et. al, 2021). The program intends to provide independence, reduce the need for nursing home services, have a positive economic impact, and improve the provision of care services

(Helsedirektoratet, 2012). The program is based on the objectives of the coordination reform regarding the role of municipalities in providing preventive services, through low threshold initiatives, and early intervention measures (Ministry of Health and Care Services, 2009).

During the initial part of the program, the Directorate of Health selected 34 municipalities out of 200 that wanted to be part of the program, it also managed the grants that the municipalities would employ to implement the program (PA, 2014). Within the governance structure of the program, the Directorate recommends the creation of a municipal innovation guide (*Komunal Innovasjonpådriver*), a public unit that oversees the organization and management of investments, contracts, grants, and the assessment of projects (Helsedirektoratet, 2012).

Since the implementation of the project varies in each municipality, there are differences between the technology that each municipality adopts and its target population. Yet, most of the projects share common features such as the use of smart home devices, alarms and monitoring sensors. Some of these projects have shown promising results in improving quality of life and reducing the burden on municipal services. Despite this potential, the systematic quantitative assessment of these projects remains unexplored.

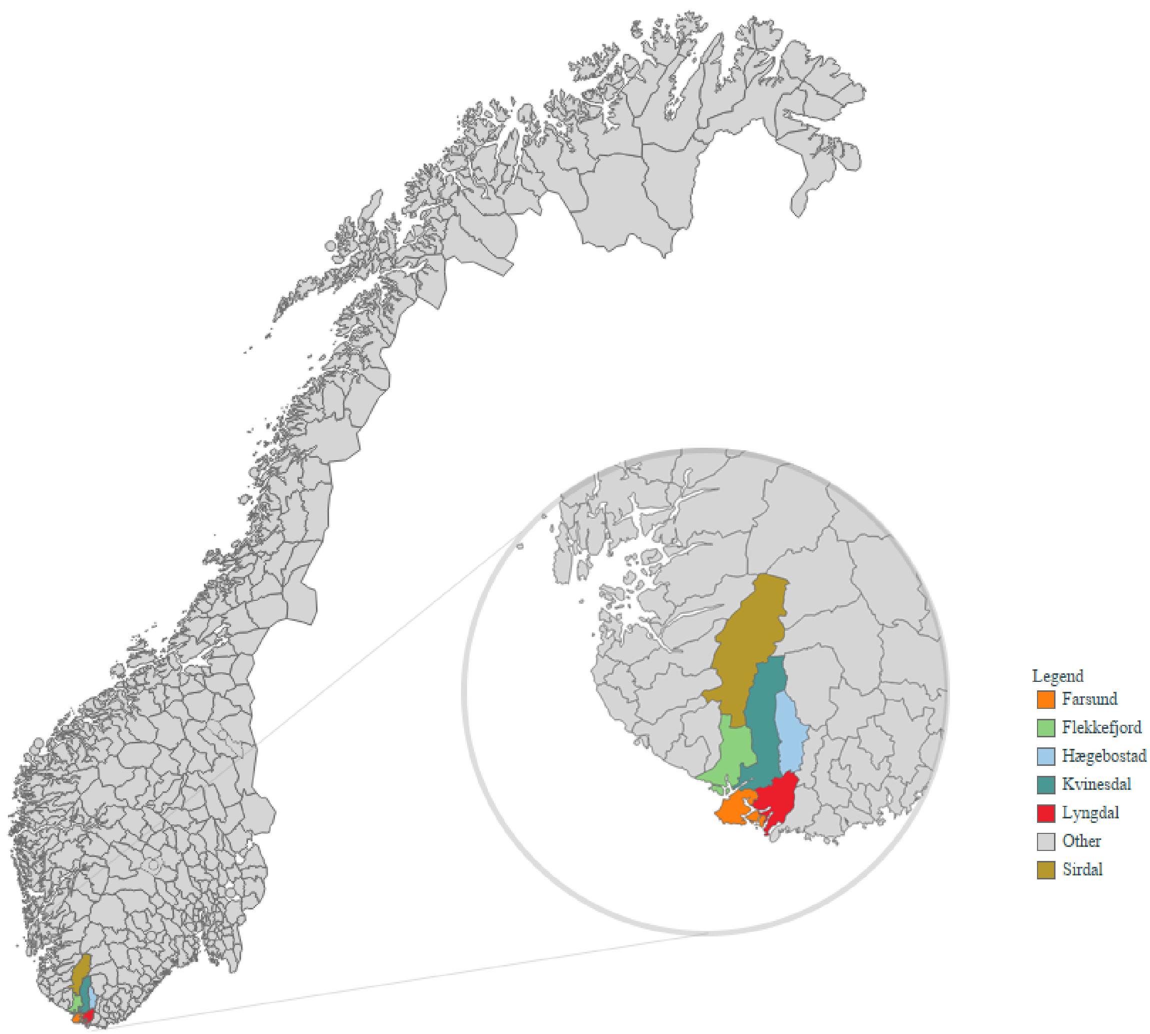
During its implementation, the program prioritized the adoption of security packages in accordance with Ministry of Health and Care Services (2011). A security package is an extension of a safety alarm that consists of self-triggering sensors, detectors, and alarms (Ministry of Health and Care Services, 2009). One advantage of these solutions in contrast to localization technologies is that they raise little ethical or legal issues since security packages are considered non-intrusive and constitute little interference with the person's privacy (Ministry of Health and Care Services, 2013b).

One of the first projects within the NWTP started in 2011 in the municipality of Lindås. The project involved the municipality, the provider of telecare services, and an academic institution that evaluated the program (Borge, 2013). According to Bjørkheim et al. (2016), in 2015 the net operating expenses for nursing and care services in Lindås had been reduced by approximately NOK 14.2 million, compared to 2014. The authors argue that these results could be attributed to the decrease in hospital admissions, reduced expenses for patients ready for discharge, and the reduced need for institutional space. However, they recognize that these findings do not answer whether the reduction responds to the introduction of the program.

2.5 Independent Living and the security packages: The region of Lister:

In 2013 the region of Lister, a region with about 13% of its population over the age of 65, which consists of the municipalities of Farsund, Flekkefjord, Hægebostad, Kvinesdal, Lyngdal, and Sirdal (See figure 2) started to execute welfare technology projects as part of the NWTP. The projects Independent living and the home security packages aim to allow individuals to live longer outside nursing home institutions and houses of care (PA, 2014). To implement the project and to improve the quality through better services and better practice the region received funding from the Sørlandedt's Competence Fund (Helsedirektoratet, 2012).

Figure 2: Municipalities in the Lister Region



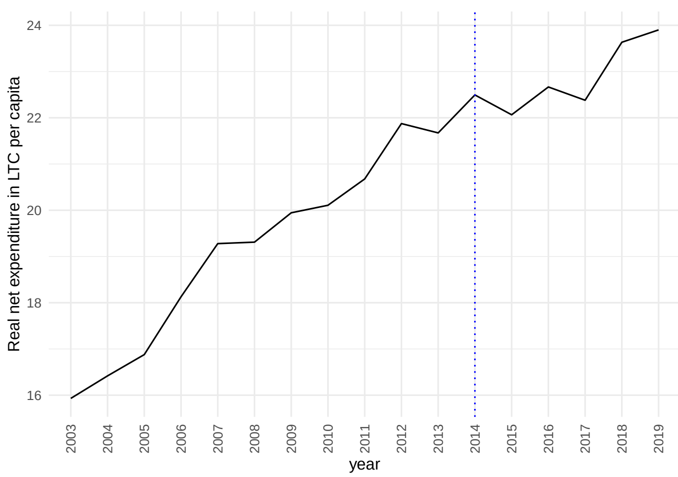
According to Røhne, Svagård, & Holmesland (2016) the implementation of the program started in the year 2014. At the core of the program was the installation of a total of 300 security packages in the houses of elderly people. This number represents around 14.9% of the population receiving HBC and NH in the municipalities of Lister in 2016. The authors indicate that these security packages included security alarms, motion-activated lights, stove guards, temperature control, camera inspection, and cognitive aid linked to smart home functions. Though the implementation of the security packages in each municipality differs, they are common in the use of security alarms such as bed alarms and door alarms. When triggered, these alarms alert municipal care services that the person has left bed or home at a given time. These functions have the potential to reduce the need for regular visits and provide more independence to the users. To participate in the project, users applied to receive the security packages, then the municipality would allocate the packages after an evaluation of user needs (PA, 2014). Ultimately, the project's quantifiable goals were to reduce the need for NH spaces and HBC services in addition to the reduction in the number of working hours in nursing homes (Røhne, Svagård, & Holmesland, 2016).

Data from Statistics Norway show that the region has reduced the average number of spaces in nursing home institutions alongside an increase in the number of users of HBC (See figure 4). In 2007, the region had on average 72.25 bed spaces in nursing homes; compared to 51.5 when the program was introduced, showing a reduction of 28.7% in the number of bed spaces. Using the number of spaces as a percentage of the population aged 80 years and over, the region shows a decline from 28.44 to 18.18 percent. In contrast, the data for HBC shows an 18.45 % increase in the number of users of these services between 2003 and 2014, when the program was implemented.

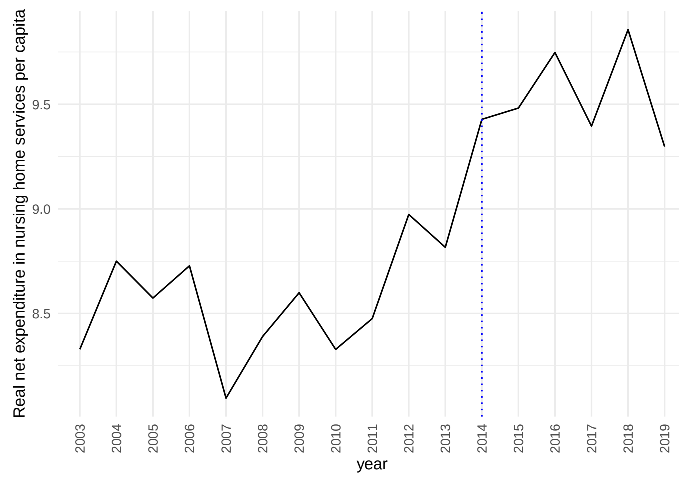
The region shows overall increases in the measures of health expenditures according to yearly data from 2003 to 2019 (See Figure 3). In Lister, the level of real net expenditures per capita in 1000 NOK shows an increase of 40% between 2003 and 2014. Expenditures in nursing homes and HBC services show similar results, with increases of 13.22% and 76.66%, respectively.

Figure 3: Mean net expenditures per capita by type of service in the region of Lister Measured in 1000 NOK and adjusted for inflation (2015=100)

(a) (Mean LTC real net expenditures per capita)



(b) (Mean NH real net expenditures per capita)



(c) (Mean HBC real net expenditures per capita)

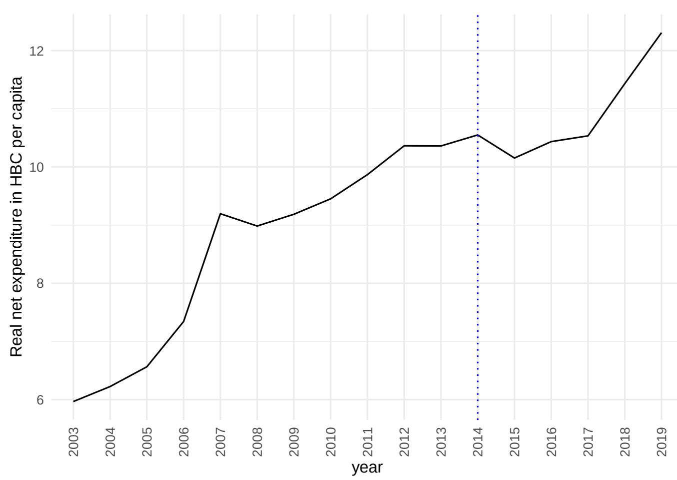
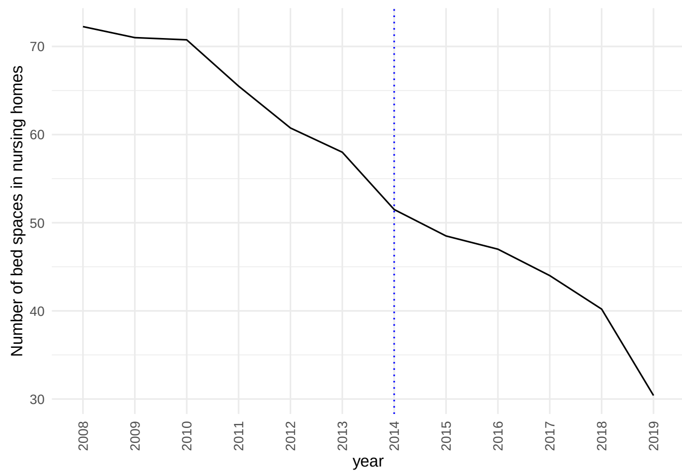
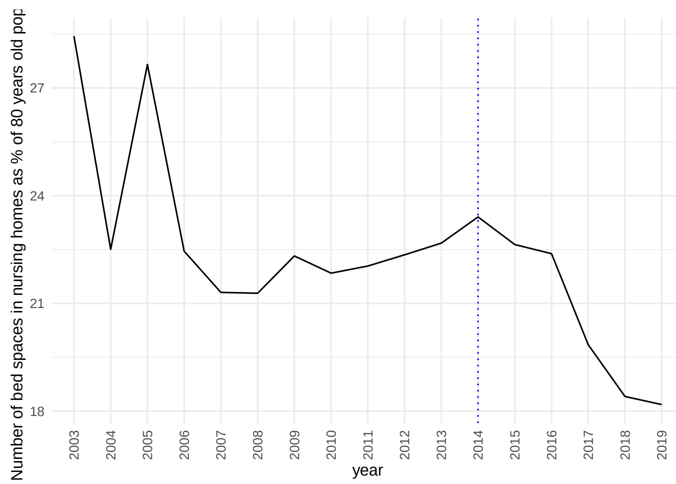


Figure 4: Utilization of LTC services in the municipality of Lister

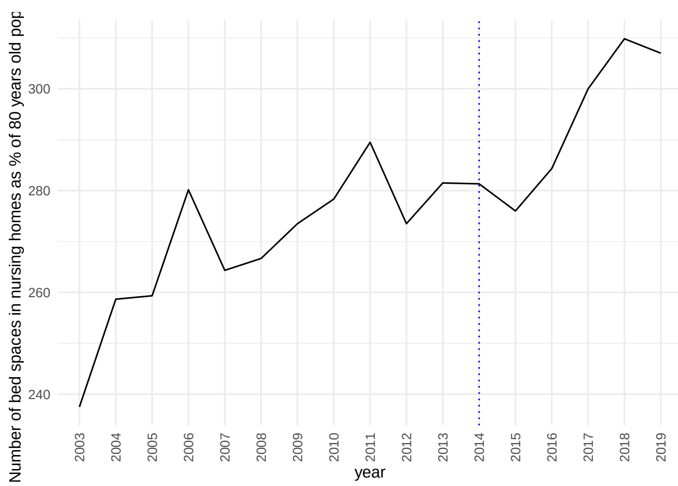
(a) (Mean number of spaces in nursing homes)



(b) (Mean number of spaces in nursing home institutions as percentage of the population aged 80 and over)



(c) (Mean number of of users of home-based care services)



3 Data and Methods

In this thesis, I estimate the effects of security packages in the region of Lister. To estimate the treatment effects of the program, I use a panel of aggregated municipal-level data from Statistics Norway that is based on annual reports from each municipality. This section provides a description of the data sources, descriptive statistics, and the methods used to evaluate the introduction of the care technology.

3.1 Sampling and treatment assignment

The dataset contains 6001 observations over 354 municipalities. Six of these municipalities belong to the treatment group, namely the municipalities of Farsund, Flekkefjord, Hægebostad, Kvinesdal, Lyngdal, and Sirdal. 29 Municipalities were dropped from the dataset because they had implemented similar projects of welfare technology during the study. Similarly, 40 municipalities were dropped due to missing values during the whole period. The observed period corresponds to the years from 2003 to 2019. Variables retrieved from the Norwegian Patient Register (NPR) contain quarterly information starting from the year 2007 to the second quarter of 2021. This data has been aggregated to contain yearly observations. A summary of the data sources is provided in table 1.

Table 1: Variables and data sources

Variable	**Period**	**Source**	**Table**
Population figures (By age group and sex)	2000-2021	Statistisk sentralbyrå	07459
Urban Population figures	2000-2021	Statistisk sentralbyrå	04861
Number of commuters	2000-2020	Statistisk sentralbyrå	11616
Users of health care services (Institutions, Home-Based care, Nursing Homes)	2008-2020	Statistisk sentralbyrå	12003;12292
Number of municipal beds	2003-2020	Statistisk sentralbyrå	13232
Net Operating expenditures	2003-2020	Statistisk sentralbyrå	05065;12367
Consumer Index Prices (2015 = 100)	2000-2020	Statistisk sentralbyrå	03013
Municipality State Reporting:	2000-2020	Statistisk sentralbyrå	11820
Deaths	2000-2021	Statistisk sentralbyrå	12983
Use of specialist health services	2010-2021 (Yearly)	Norsk pasientregister	Aktivitet i somatiske sykehus

3.2 Outcome Variables

The set of dependent variables in this analysis is divided into three categories: healthcare utilization, health outcomes, and economic outcomes. Healthcare utilization variables relate to the use of nursing homes (NH), specialized care, LTC institutions, and HBC services. Health-outcome variables include age-specific mortality and mortality per 1000 inhabitants, whereas economic outcomes include real expenditures in long-term care institutions, nursing homes, and home-based services. I used R to perform data cleaning and manipulation tasks.

3.3 Descriptive statistics

Tables 2 to 5 provide a summary of descriptive statistics on economic and health outcomes. Both groups show similarities in terms of average real expenditures per capita by type of health services. Similarly, in terms of average healthcare utilization measures, I find good balance between treated and control groups across all measures of Interest. However, in contrast to the mortality rate per 1000 inhabitants, age-specific measures of mortality show important differences between the averages of the treated and control groups (See table 5). To examine pre-treatment balance, I use 2013 as a baseline of pre-treatment measures. At the baseline, I find good balance in all average outcome measures between the two groups (See table 6). Similar to previous figures, age-specific measures of mortality show wide differences between treated and control at the baseline.

Table 2: Descriptive Statistics: Real Expenditures per type of Health Service

		Group	N	Mean	SD	Min	Q1	Median	Q3	Max
1	Long term care services	Control	5875	18.77	6.43	0.11	14.17	17.85	22.36	57.74
1.1		Treated	102	20.43	5.72	11.82	16.42	18.89	22.69	36.80
2	Nursing home services	Control	5875	8.40	4.16	0.27	5.58	7.52	10.33	51.95
2.1		Treated	102	8.90	4.90	2.14	5.95	7.10	9.27	23.52
3	Home based care services	Control	5875	8.48	3.88	0.09	5.99	7.95	10.36	44.79
3.1		Treated	102	9.35	3.05	4.64	6.87	8.85	10.68	16.58

Notes:
[1] Source: Statistics Norway (2022)
[2] Real expenditures in LTC services are expressed in 1000 NOK
[3] All figures have been adjusted for inflation using 2015 a as a base year

Table 3: Descriptive Statistics: Users of long term care services

		Group	N	Mean	SD	Min	Q1	Median	Q3	Max
1	Number of beds in NH per 1000 inhabitants	Control	5875	11.61	5.58	0.00	7.53	10.91	14.69	43.72
1.1		Treated	102	11.68	5.98	3.70	6.40	10.13	15.01	23.60
2	Users in full-time dwellings	Control	3301	54.46	70.55	0.00	14.00	31.00	65.00	700.00
2.1		Treated	50	54.20	22.27	0.00	43.00	56.00	70.00	94.00
3	NH Utilization (80+ population)	Control	5875	20.90	8.61	0.00	16.33	20.00	23.86	114.29
3.1		Treated	102	22.34	10.15	8.30	14.56	18.78	33.33	42.86
4	HBC utilization rate (80+ population)	Control	5777	36.58	7.21	0.00	31.88	36.05	40.69	84.35
4.1		Treated	102	36.90	7.59	21.21	32.31	35.79	41.20	65.67

Notes:
[1] Source: Statistics Norway (2022)
[2] The number of beds in nursing homes are expressed as units per 1000 inhabitants
[3] The number of users in nursing home spaces corresponds to the period 2007-2019 and does not consider the municipalities of Sirdal and Hægebostad
[4] NH and HBC utilization rates are expressed as percentages of the population aged over 80 year

Table 4: Descriptive Statistics: Hospital admissions

		Group	N	Mean	SD	Min	Q1	Median	Q3	Max
1	Hospital admisions (%61-70 years old)	Control	3936	1.53	0.36	0.00	1.28	1.51	1.75	3.10
1.1		Treated	72	1.52	0.24	0.77	1.40	1.56	1.66	1.98
2	Hospital admisions (%71-80 years old)	Control	3936	4.06	1.18	0.00	3.24	3.88	4.69	9.03
2.1		Treated	72	3.90	0.95	1.77	3.23	3.71	4.41	6.35
3	Hospital admisions (%80 years old and over)	Control	3936	0.48	0.15	0.00	0.39	0.47	0.57	1.18
3.1		Treated	72	0.51	0.11	0.29	0.43	0.50	0.61	0.69

Notes
[1] Source: National Patient Registry (2022)
[2] Hospital admissions are scaled to the size of each population age group and correspond to the period 2010-2021

Table 5: Descriptive Statistics: measures of mortality

		Group	N	Mean	SD	Min	Q1	Median	Q3	Max
1	Death rate per 1000 inhabitants	Control	5882	10.21	3.29	0.0	7.9	9.85	12.0	27.0
1.1		Treated	102	9.64	2.04	5.3	8.2	9.50	10.8	17.1
2	Number of deaths 65-79 years	Control	5882	20.58	28.66	0.0	6.0	11.00	23.0	247.0
2.1		Treated	102	15.01	8.84	1.0	6.0	15.00	22.0	39.0
3	Number of deaths 80+ years	Control	5882	44.11	61.63	0.0	14.0	25.00	48.0	624.0
3.1		Treated	102	33.17	19.45	1.0	13.0	34.00	51.0	70.0

Notes:
[1] Source: Statistics Norway (2022)
[2] Death rate expressed as deaths per 1000 in each municipality
[3] Age specific measures of mortality correspond to the total number of deaths in that age group

Table 6: Descriptive Statistics: Baseline measures (Year 2013)

		Group	N	Mean	SD	Min	Q1	Median	Q3	Max
1	Real Expenditures in LTC (1000 NOK)	Control	2413	15.78	5.21	5.38	12.19	15.08	18.45	54.47
1.1		Treated	42	17.98	5.19	11.82	14.07	16.81	18.87	30.20
2	Real Expenditures in NH (1000 NOK)	Control	2413	7.41	3.42	1.45	4.92	6.87	9.16	29.75
2.1		Treated	42	8.49	4.12	2.14	5.91	6.99	9.11	18.86
3	Real Expenditures in HBC (1000 NOK)	Control	2413	6.82	3.21	0.56	4.95	6.40	8.09	40.89
3.1		Treated	42	7.64	2.41	4.64	6.23	7.32	8.58	15.83
4	Number of beds in NH per 1000 inhb.	Control	2408	11.84	5.40	0.00	7.78	11.24	14.78	43.72
4.1		Treated	42	12.87	5.97	3.88	8.91	11.39	16.09	23.60
5	NH Utilization (% 80+ population)	Control	2408	21.45	8.33	0.00	16.86	20.58	24.48	100.00
5.1		Treated	42	23.71	9.40	9.20	17.88	21.87	30.45	42.86
6	HBC utilization rate (% 80+ population)	Control	2379	38.15	8.09	0.00	33.33	37.58	42.24	84.35
6.1		Treated	42	37.30	9.61	21.21	32.28	36.42	40.56	65.67
7	Death rate per 1000 inhabitants	Control	2413	10.55	3.33	2.20	8.30	10.20	12.40	27.00
7.1		Treated	42	10.31	2.14	6.80	8.80	9.90	11.10	17.10
8	Number of deaths 65-79 years	Control	2413	20.34	28.31	0.00	6.00	11.00	22.00	240.00
8.1		Treated	42	14.24	7.77	2.00	6.00	15.00	20.00	28.00
9	Number of deaths 80+ years	Control	2413	43.59	59.79	0.00	14.00	26.00	47.00	548.00
9.1		Treated	42	33.90	18.65	7.00	15.00	33.00	51.00	70.00

Source Statistics Norway (2022)

3.4 Methods

The objective of this thesis is to estimate the causal effects of the adoption of the security packages in Lister. To do this, I rely on recent developments in causal identification strategies. Causal inference is the use of knowledge and theory to estimate the effect of an event on an outcome of interest (Cunningham, 2021). Identifying causal effects requires information about the population in the presence and the absence of interventions, namely values of counterfactual outcomes (Hernán & Robins, 2019).

In the evaluation of policies, counterfactuals are usually constructed by conducting a Randomized Control Trial (RCT), an experiment in which both control and treatment groups are selected randomly so that, on expectation, they are identical and any observed difference between them can be attributed to the treatment (Gertler et al., 2016). As a result, randomization makes treatment status independent of potential outcomes and produces comparable units; Thus eliminating selection bias (Angrist & Pischke, 2008; Haynes et al, 2012). However, when observational data is the only information available, it is possible to answer causal questions by identifying sources of exogenous variation and using the right estimation technique (Angrist & Krueger, 1999).

About these identification strategies, Cunningham (2021) explains that to make causal claims under this framework our problem needs to be framed so that the stable unit treatment value assumption holds. This assumption rules out externalities and different versions of treatment (Imbens & Rubin, 2010). In the context of this thesis, this means that the implementation of the program does not affect untreated units. It is possible to imagine a situation where this assumption does not hold. For instance, one could imagine municipalities following initiatives that they consider beneficial to their population once another municipality has implemented it successfully. Similarly, the assumption requires that the treatment is homogeneous across units. In this context, this requires all municipalities to receive the same type of technology or the same quantity.

In practice, randomization is not always possible for administrative, ethical, or economic reasons. However, in the absence of actual randomization, it is still possible to estimate treatment effects under the right experimental design. Causal identification strategies such as

Difference in Differences (DiD), Propensity Score Matching (PSM), and Synthetic Control Methods (SCM) provide researchers the tools to obtain comparable units and identify causal effects.

However, these methods rely on a set of assumptions that need to be satisfied before establishing causal claims. For example, the estimation of causal effects through the use of DiD, which has become widespread in the empirical literature, relies on the assumption that in the absence of treatment both groups would have followed a similar trend over time; this is called the parallel trends assumption (Abadie, 2005; Angrist & Pischke, 2014). This causal identification strategy is commonly used in settings where randomization is not feasible or unethical. In health care, for instance, it has been used to evaluate changes in policy regarding alcohol regulation, cigarette taxation, provision of health care services, reduction in out-of-pocket payments, etc (Wing, Simon, & Bello-Gomez, 2018).

However, concerns over the use of DiD to estimate causal effects include the consistency of the Standard Errors of the DiD estimator and the presence of parallel trends. Concerns over standard errors relate to the nature of the data in panel data settings. Panel data often contains information that is serially correlated. Because of this correlation, data contains less information on random variations of any variable in the analysis. To miss random variation on outcome variables results in standard errors that miss to capture the actual variability of our estimators under random sampling (Angrist & Pischke, 2014). In addition, in many settings the parallel trends assumption does not hold, which implies that DiD will not identify the causal effect of interest.

In this paper, I will use a variation of the initial SCM by Abadie & Gardeazabal (2003) developed by Ben-Michael, Feller, & Rothstein (2021) called the Augmented Synthetic Control Method. It relies on the same assumptions of the initial SCM framework, yet, includes the possibility to estimate treatment effects for multiple treated units with different adoption periods, while adjusting for unit and global imbalances over time.

3.5 Identification Strategy

3.5.1 Synthetic Control Method

Recent developments in the methods used to conduct comparative studies provide useful tools to estimate causal effects in instances where there is no appropriate control group. This thesis focuses on the literature built upon the work of Abadie & Gardeazabal (2003), Abadie, Diamond, & Hainmueller (2010) and Abadie, Diamond, & Hainmueller (2015), Ben-Michael, Feller, & Rothstein (2019) on Synthetic Control Methods (SCM).

These methods rely on a similar framework of the difference-in-differences estimatiors but combine it with matching on pre-treatment observations (Huntington-Klein, 2021). While performing this matching process, SCM chooses weights for control units based on an optimization algorithm. The result is a unit that resembles the pre-treatment period of the treated and that is assumed to provide a good counterfactual in the post-treatment period. This counterfactual is called a synthetic control, and the difference between the observed outcomes of the treated unit, and the outcomes estimated through the synthetic control represent the treatment effect of the intervention. Recent developments in synthetic methods include Generalized Synthetic Control Methods, Synthetic Differences in Differences, and Augmented Synthetic Control (Arkhangelsky, Athey, Hirshberg, Imbens, & Wager, 2019; Ben-Michael, Feller, & Rothstein, 2019; Xu, 2017).

Following the notation in Abadie (2021), the SCM denotes the causal effect of an intervention as $\alpha_{it} = Y_{it}^I - Y_{it}^N$, where the superscript I denotes the exposure to the intervention; therefore Y_{it}^I is the outcome after the intervention was introduced for unit i at time t, whereas the superscript N refers to the absence of treatment. Then, Y_{it}^N is the outcome in the absence of the intervention. The SCM relies on two assumptions: 1) there is no anticipation of the treatment, one that could affect the outcome variable prior to the intervention, this assumption implies $Y_{it}^I = Y_{it}^N$ 2) there is no externalities, meaning that the intervention only affects those in the treatment group.

The SCM assumes that the outcome variable Y_{it}^N is given by the model

$$Y_{it}^N = \delta_t + \theta_t Z_i + \lambda_t \mu_i + \epsilon_{it} \tag{1}$$

where δ_t is a time-specific factor, Z_i is a vector of observed predictors of Y_{it}^N, θ_t is a vector of time-specific coefficients, μ_i is a vectors of unit-specific unobserved predictors of Y_{it}^N, and λ_t is a vector of time-specific factor loadings. Finally, ϵ_{it} is the error term, that denotes unobserved transitory shocks (Abadie, 2021)..

Similarly, the SCM setup considers a (J x 1) vector of weights, where J denotes the number of units. This vector of weights is $W = (w_2, \ldots, w_{j+1})$, where $w_j \geq 0$ and $w_2 + \ldots + w_{j+1} = 1$. The values in W represent a potential synthetic control, and is a weighted average of control units. As a result, the outcome of interest for the synthetic control unit will be indexed by the weights in W, that is:

$$\sum_{j=2}^{J+1} w_j Y_{jt} = \delta_t + \theta_t \sum_{j=2}^{J+1} w_j Z_j + \lambda_t \sum_{j=2}^{J+1} w_j \mu_j + \sum_{j=2}^{J+1} w_j \epsilon_{jt} \tag{2}$$

Thus, the estimated treatment effect is denoted by $Y_{it}^I - \sum_{j=2}^{J+1} w_j^* Y_{jt}$. Where w_j^* is the selected value that minimizes $||X_0 - X_0 W||$.

3.5.2 Augmented Synthetic Control Methods (ASCM)

Developing upon the original framework by Abadie & Gardeazabal (2003), Abadie, Diamond, & Hainmueller (2010) and Abadie, Diamond, & Hainmueller (2015), Ben-Michael, Feller, & Rothstein (2021);(2019) have developed an Augmented variation of the initial SCM that extends to cases where is impossible to find a synthetic control. Additionally, the Augmented Synthetic Control Methods (ASCM) extend the SCM to multiple treated units with different treatment times. Similar to the initial SCM, the ASCM constructs a counterfactual from pre-treatment outcomes and characteristics of the donor pool. If this synthetic control resembles the pre-treatment trend of the treated, then it is assumed that it is a good counterfactual for the post-treatment period.

The ASCM is a modified version of the SCM estimator that adjusts for poor pre-treatment fit. As a result, the ASCM includes an estimator $\hat{m}_{it}$ that is a function of pre-treatment outcomes. That is

$$Y_{it}^{aug}(0) = \sum_{Wi=0} \hat{\gamma}^{scm} Y_i t + (\hat{m} - \sum_{Wi=0} \hat{\gamma}^{scm} \hat{m}_{it}). \tag{3}$$

Equation (3) highlights the motivation behind the ASCM, it corrects the SCM estimate by the imbalance in the function of pre-treatment outcomes $\hat{m}(.)$. This correction is analogous to bias correction due to inexact matching (Ben-Michael et al, 2019). This way, the SCM weights are corrected through a parameter that accounts for the unit i-specific transformation of linear lagged outcomes that depend on the weighting function $\alpha(.)$:

$$\hat{Y}(0) = \sum_{Wi} (\hat{\gamma}^{scm} + \hat{\gamma}^{adj}) Y_{iT}, \ where \ \hat{\gamma}^{adj} \equiv \hat{\alpha}_i(X) - \sum_{Wi} \hat{\gamma}^{scm} \hat{\alpha}_i(X_i) \tag{4}$$

As a result of this correction, the weights expressed by the $\hat{\gamma}^{adj}$ can be also negative, a departure from the SCM weights that are constrained only to positive values. The authors mention that this is relevant to the composition of the donor pool, which contrasts with the SCM by including a higher number of units in the donor pool due to negative weighting.

Similarly, to include more than one treated units, the ASCM can take three different forms 1) Fit separate SCM for each treated unit, 2) Fit a single aggregated SCM 3) Estimate an SCM by fitting a pooled estimator. In this regard, Ben-Michael, et. al (2019) elaborate on the drawbacks of estimating separated models or computing an aggregated model. According to the authors estimating separate estimators and averaging their ATT estimates produces a poor fit for the average of treated units; whereas a pooled estimation produces a poor fit at the municipal level. The solution then is to estimate the ATT by computing unit weights that reduce unit-specific imbalance and pooled imbalance. This is given by:

$$\min_{\hat{\gamma}_1,\ldots,\hat{\gamma}_j \in \Delta^{scm}} = \frac{\nu}{2} q^{pool}(\Gamma) + \frac{(1-\nu)}{2} q^{sep}(\Gamma) + \lambda \sum_{j=1}^{J} \sum_{i=1}^{N} f(\gamma_{ij}) \tag{5}$$

where ν represents the hyperparameter that corresponds to both the solutions of a separate

SCM ($\nu = 0$) and an aggregated SCM approach ($\nu = 1$). Intermediate values of ν correspond to a partially pooled solution for the SCM weights.

3.6 Estimation

To capture the causal effect of the care technology I estimate an augmented synthetic control model for the municipalities in the region of Lister. In this thesis, I use 2014 as treatment time T since it is the first year of the implementation period. The introduction of the security packages started in the year 2014 and the adoption concluded in the year 2016 (Røhne, Svagård, & Holmesland, 2016).

The ASCM was initially estimated using outcome variables as matching variables following Ben-Michael, Feller & Rothstein (2019;2021). To estimate the ATT I used a set of dependent variables that relate to the project's objective, namely, real net expenditures per capita in LTC, utilization of institutional space, and the use of specialist care services. Additionally, I include a set of estimations that include measures of mortality. After estimating the ATT using outcomes as matching criteria, I use a set of independent variables as additional matching characteristics. The selection of auxiliary covariates included variables from the Local Authorities reporting system (KOSTRA) in Statistics Norway (2022).

4 Results

In this section, I present the results from the different estimations coming from the ASCM. First, I present the results that correspond to the different outcome models that match only on pre-treatment outcomes following the basic setup by Ben-Michael, Feller, & Rothstein (2019). Then, to explore any variations after balancing for pre-treatment characteristics, I present the results including auxiliary covariates for measures of expenditures and utilization of LTC. I present robustness tests in the next section.

4.1 Net expenditures by type of health service

The first ASCM estimates of this thesis address the effects of the intervention on real per capita expenditures. This measures are expressed in 1000 Norwegian Kroner (NOK) and were adjusted for inflation using 2015 as a base year. The rationale behind this estimation is that the introduction of care technologies allows municipalities to reduce expenditures on LTC services, nursing homes, and HBC services through the increased independence of users and the reduction of needs for institutional spaces.

Preliminary results on economic outcomes show an increase of 592 Norwegian Kroner (NOK) in the average real per capita expenditure on LTC care services. Tables 7 to 9 in the appendix summarize the estimates of the ATT for each period after the technology was implemented. Similarly, estimations for NH and HBC services, show small increases of 343 and 89 NOK in the average the level of expenses. These estimates represent a small proportion of the actual expenses in the region. From 2003 to 2019 the average level of real per capita expenditures in LTC was 18770 NOK. Average real per capita expenditures in NH and HBC were around 8480 and 8400 NOK respectively.

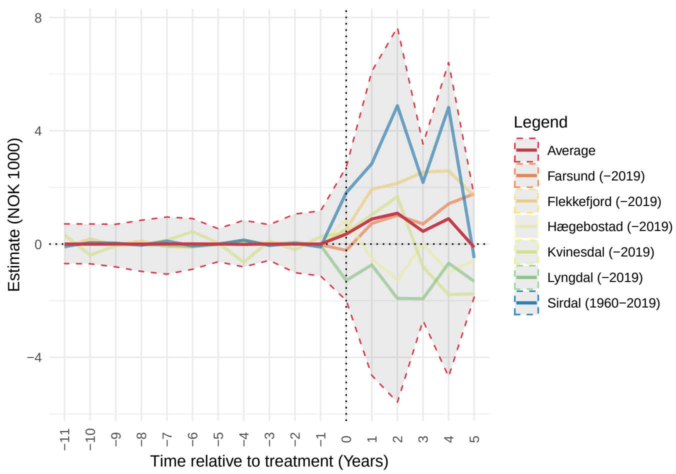
Global measures of pre-treatment imbalance between the synthetic and observed average show measures of 5, 7, and 10 NOK for the expenditures in LTC services, nursing homes, and home-based-care services respectively. Figure 5. shows the ATT estimates for the level of real per capita expenditures in LTC, showing a good pre-treatment fit for the synthetic average in each of the three types of health services.

At the municipal level the pre-treatment imbalance is much higher, with measures of imbalance of around 138, 241, and 418 NOK in expenditures for LTC, NH, and HBC services respectively. As shown in figure 5, although the ASCM estimations produce a good pre-treatment fit, the results do not provide statistically significant results, with wide confidence intervals containing zero values in each of the estimations.

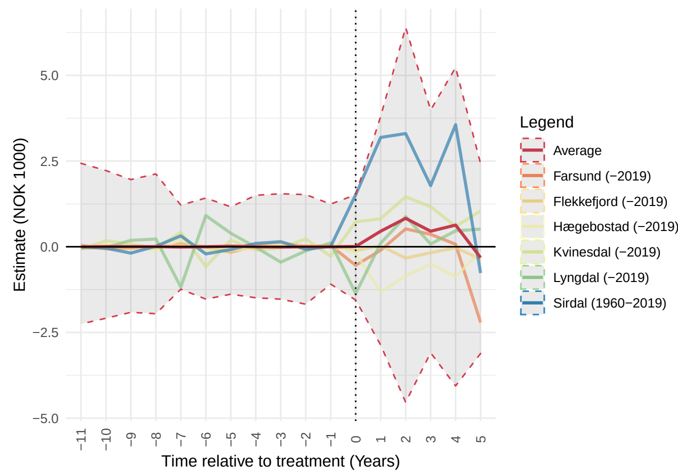
The inclusion of auxiliary covariates to weight based on pre-treatment characteristics includes demographic variables such as population size, the percentage of the population aged 80 and over, percentage of the urban community, the life expectancy of men and women, and the average travel time to the city center. Estimates of the ATT show an increase in per capita expenditures in LTC by 536 NOK. Similarly, when balancing for these covariates, estimates for nursing homes and home-based care services show an increase of 492 and 29 NOK respectively. Figure 10 in the appendix shows the ATT estimates after treatment was implemented for the specifications including covariates in the model.

Figure 5: ATT estimates by type of health expenditure

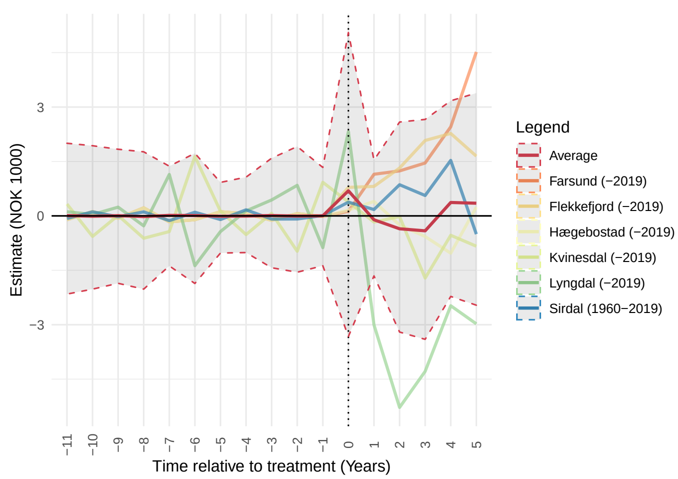
(a) (Real net expenditures in Long Term Care Services)



(b) (Real net expenditures in Nursing Home Services)



(c) (Real net expenditures in Home Based Care Services)



4.2 Utilization of health care services

4.2.1 Long Term Care Services

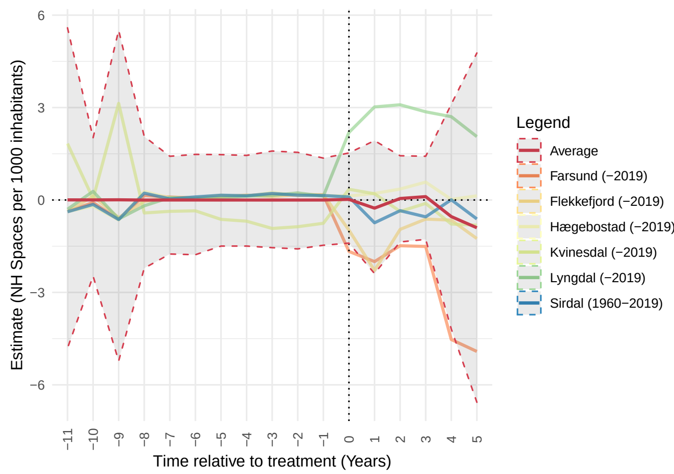
Estimations of the use of nursing homes and home-based care services show overall increases in the number of users; the number of nursing home beds per 1000 inhabitants increased by 2.54 units on average after the treatment was introduced. In contrast, I find a reduction of 0.23% in the number of spaces in NH as a percentage of the population aged 80 years and above. Results of home-based-care services, show an average increase of 2.3% in the percentage of HBC users aged 80 and over. Conversely, the number of users in full-time dwellings as a percentage of the total population shows an average reduction of 0.2% users in the treated group. As figure 6 shows, confidence intervals around the estimations of pre- and post-treatment outcomes show non-significant results for both the average synthetic control and the municipal units.

Measures of global imbalance between the treated and its synthetic control show almost zero imbalance for all the measures of LTC services (See figure 6). In contrast, measures of municipal imbalance show a wide variation between treated units and their respective synthetic controls. Tables 10 to 12 in the appendix summarizes the estimates of the ATT for each period after the technology was implemented

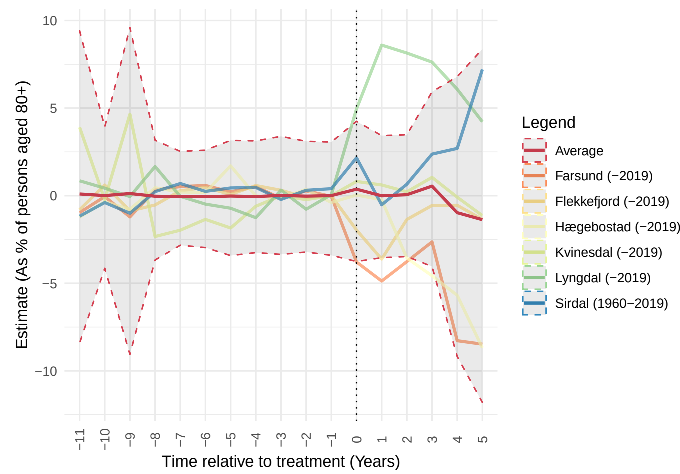
The inclusion of covariates in the model produces similar non-significant results. Incorporating auxiliary covariates results in a modest increase of 0.534 in the number of spaces per 1000 inhabitants. The estimates for the number of spaces in NH as a percentage of the population over 80 years show a small increase of 0.219%, whereas the percentage of HBC users increased by 0.5%.

Figure 6: ATT estimates by type of Care service

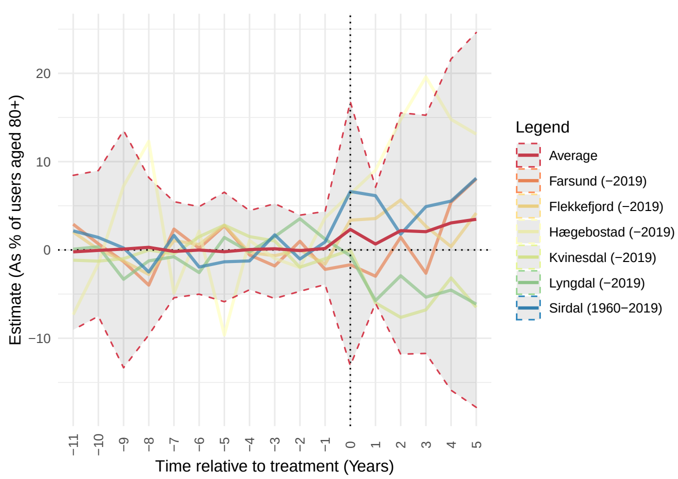
(a) (Number of spaces in Nursing homes)



(b) (Number of users in nursing homes)



(c) (Number of users in nursing homes aged 80 years)

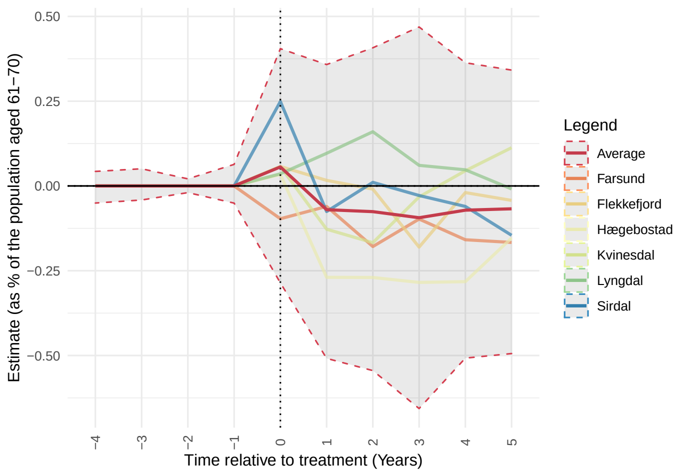


4.2.2 Specialist Care Services

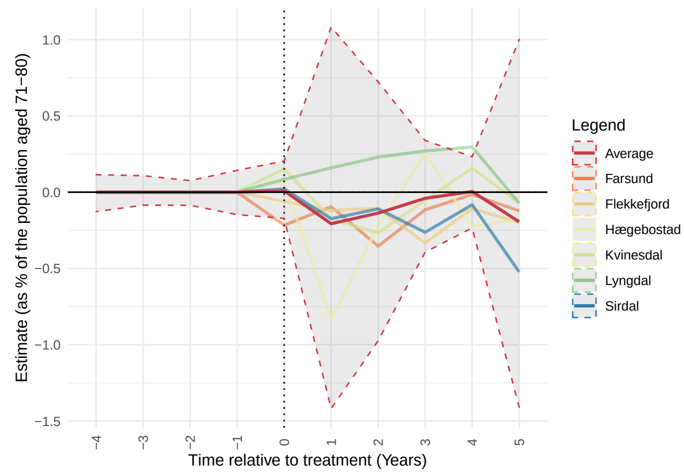
The results for the demand for specialist care services show different estimates for each age group in the data coming from the NPR. Results for the populations between 61-70 and 71-80 years show a reduction of 4.4% and 5.9% in the number of hospital admissions. Similarly, for the population above 80 years, the average estimate shows a reduction of 1.2% after the intervention started. Figure 7 depicts the evolution of the ATT from 2010 through 2019. Tables 13 to 15 in the appendix show ATT after the technology was implemented. Similar to previous estimates, though the synthetic control provides a good fit at the global and municipal level, ATT estimates show a high degree of uncertainty reflected in the wide confidence intervals around the estimates. As a result, there is no evidence of a significant effect of the program on the number of hospital admissions.

Figure 7: ATT estimates specialist care services

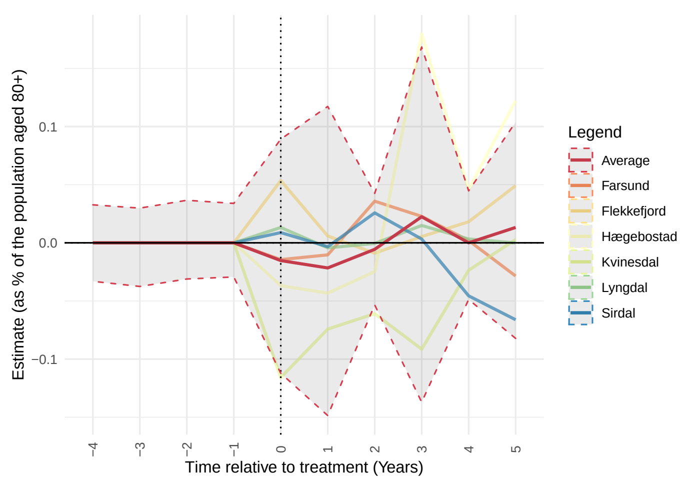
(a) (Number of patients in specialist care services - 80+ population)



(b) (Number of patients in specialist care services - 61-70 years population)



(c) (Number of patients in specialist care services - 71-80 years population)



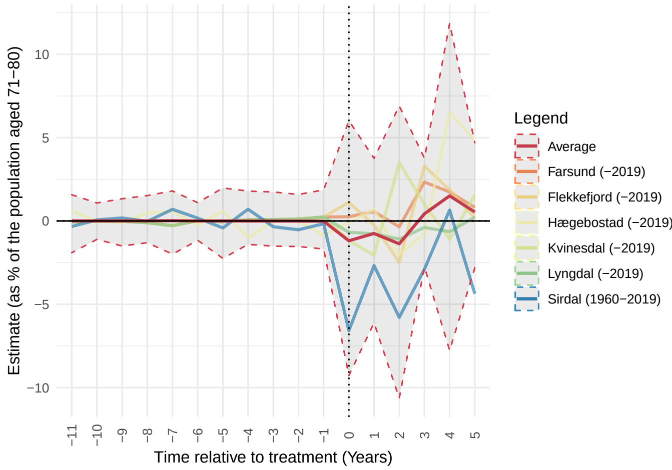
4.3 Mortality

ASCM estimates on health outcomes show a small reduction of 0.139 in the levels of mortality per 1000 inhabitants. For measures of crude mortality for populations between 65-79 years old and over 80 years, I find reductions in the number of deaths of 1.96 and 1.104 respectively. Tables 16-18 show a summary of the ASCM estimates for the post-treatment periods. Figure 8 shows the levels of global and municipal imbalance in pre-intervention periods. Despite good pre-intervention fit at the global and municipal level, the estimates for post-treatment effect show non-statistically significant effects from the program.

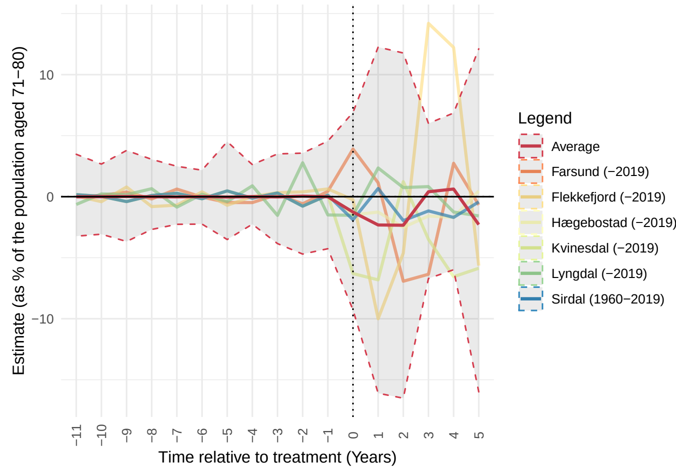
In terms of global imbalance between the treated units and the donor pool, the ASCM provides good pre-treatment balance in the three outcome variables with 0.008, 0.019, and 0.009 for mortality per 1000 inhabitants, and age-specific deaths in the 65-79 and 80 years group. Similarly, individual imbalances show near-zero imbalance figures for each of the treated units. Tables 17 to 19 in the appendix show the ATT estimates for each period after the technology was implemented

Figure 8: ATT estimates on health outcomes

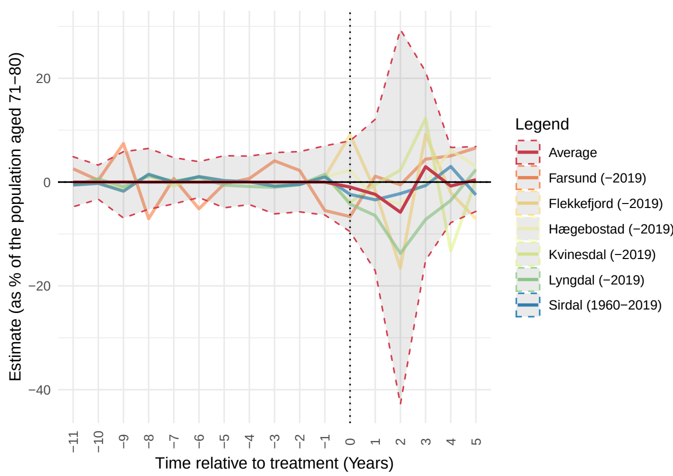
(a) (Deaths per 1000 inhabitants)



(b) (Number of deaths aged between 65 and 79 years)



(c) (Number of deaths aged 80 years)



5 Inference: Placebo simulation

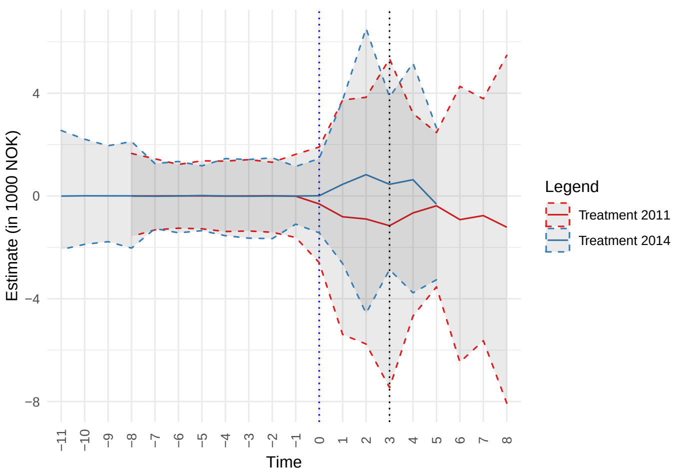
In contrast to other methods where significance is determined by assuming a particular distribution, inference in the context of synthetic control methods is based on the construction of placebo/falsification studies (Huntington-Klein, 2021). These experiments replicate variations in the time of treatment and changes in the composition of the donor pool. In principle, these placebo experiments are useful to identify causal effects and evaluate the strength of the results. If falsification experiments produce similar results to those in the baseline, then the confidence that the program had any effect would be undermined (Abadie, Diamond, & Hainmueller, 2015). In this section, I will explore changes in the estimates when the treatment time is set to an earlier year.

In Time Placebo

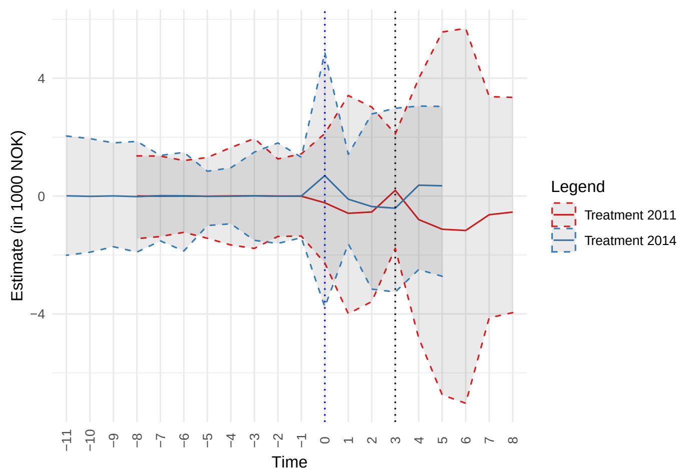
To achieve balance between the synthetic control and the treated units, the ASCM assigns weights to units in the donor pool based on pre-treatment observations. This optimization process uses the time of treatment as a reference. Therefore, to assess, these results, following Abadie, Diamond, & Hainmueller (2015) and Ben-Michael, Feller, & Rothstein (2019) I reassign treatment time to an earlier period. To estimate the in-time placebo, I will use the start of the national program as a new treatment time. For this analysis, I have considered the variables relevant to the project's objectives, namely expenditures in LTC and utilization of LTC services. Figure 9 shows the comparison between the time-placebo and the actual treatment time. Similar to previous estimations, the results show non statistically significant results in any of the categories. Also, the figure shows different trends when the treatment time is set to an earlier year. These results confirm the absence of evidence on the effects of the program.

Figure 9: ATT In Time Placebos: The figure shows a comparison between the assignment of treatment in 2011 and 2014. The vertical line in time 0 depicts the placebo treatment and the second vertical line in time 3 represents the actual tratment time

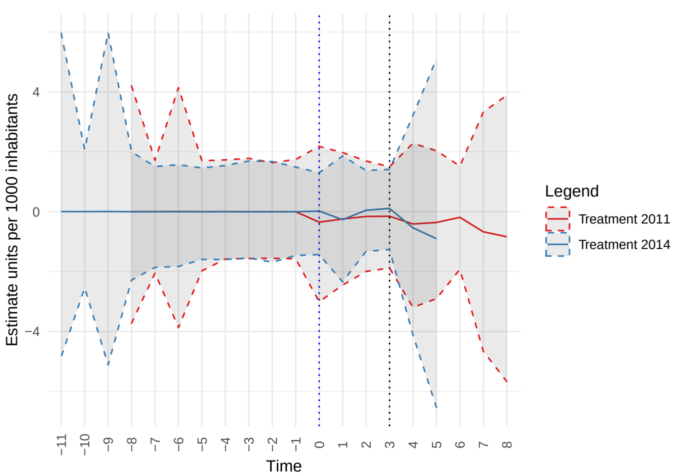
(a) (Real net expenditures in NH services)



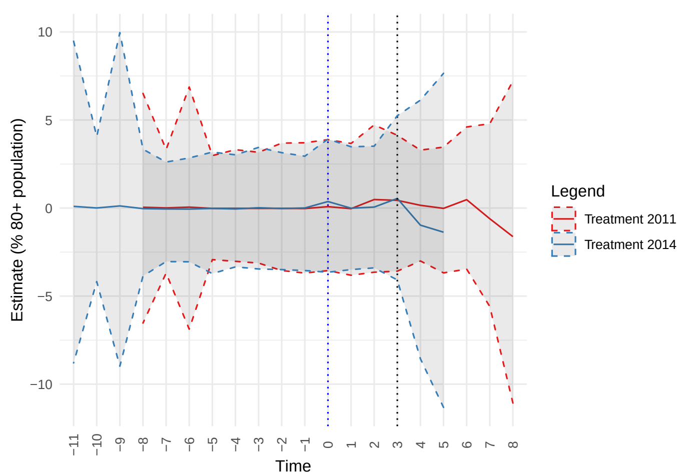
(b) (Real net expenditures in HBC)



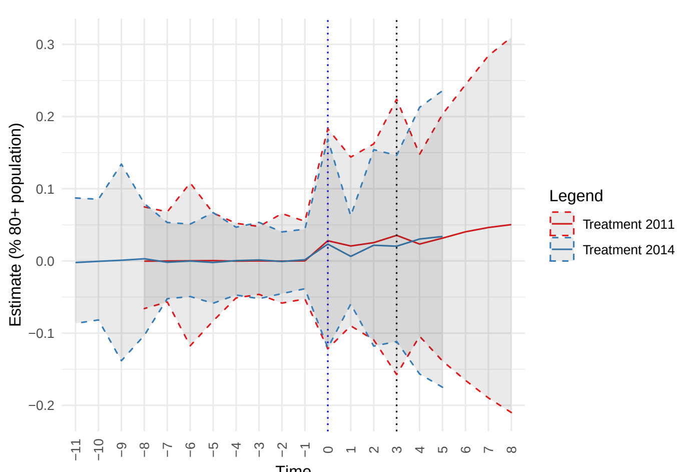
(c) (Number of beds per 1000 inhabitants)



(d) (Utilization NH - Percentage of 80+ population)



(e) (Utilization HBC - Percentage of 80+ population)



6 Conclusion

This thesis evaluated the implementation of a welfare technology program in 6 Norwegian municipalities. The program is intended to improve the use of long term care resources and reduce the number of users of home-based care and nursing homes. To answer the question of whether the program had any impact on these areas or not, I used the introduction of the program in 2014 in the Region of Lister. Then, using a sample of 354 Norwegian municipalities and an augmented synthetic control method (ASCM), I evaluated the effects of the program on long term care expenditures, utilization of long term care services, mortality, and utilization of specialized health services.

From the ASCM estimations, I find no evidence that the program affected long term care expenditures, mortality, and the utilization of specialized and municipal health services. This lack of effects is observed across all measures and different age groups. Under this setting and methods, my results show a high degree of uncertainty in each of the measures of interest. This uncertainty is reflected on the wide confidence intervals around individual and aggregate ATT estimates. The degree of uncertainty around my results limits the identification of a positive or negative effect of the program. These results challenge the hypothesis that the use of security packages helps to reduce the levels of expenditure on long term care services and the utilization of municipal long term care services. Similarly, these findings contest the hypothesis that the introduction of the security packages has any effect on mortality measures and the number of admissions to specialized health services.

The findings of this thesis are limited by different factors. First, there are potential violations of the no-externalities assumption since the national welfare technology program has grown in the recent years. The growth of the program has led multiple municipalities to incorporate similar projects during the studied period. Therefore, further research could explore ways to include new municipalities or find different ways to aggregate treated units. Second, the selection of matching co-variates in the estimates for LTC expenditures and utilization of LTC services did not follow the optimization process that minimizes the root mean square error (RMSE) meaning that better solutions in terms of balance could have been estimated.

My results contribute to the literature on the use of welfare technologies and provide multiple interpretations that can help to guide further research in this area. First, since I use aggregated municipal data, these estimates represent intention-to treat-effects, which assume that the whole target population can receive the treatment. In reality, only selected applicants receive the treatment after an assessment from municipal services. Thus, studying the project using individual-level data and using different strategies such as matching could help to evaluate causal effects more closely. Second, the adoption of the program remains small and unevenly distributed across the municipalities in Lister. Although all municipalities have adopted security packages and digital supervision as part of the program, users are assigned different technologies based on their individual needs. In this regard, further research could explore the use of welfare technology programs that target a particular diseases through comparable technologies. To summarize, this research explores the complexities behind the evaluation of these welfare technologies. These complexities are linked to the treatment of different patient groups, through new ways of coordinating and providing care. Along with the previous literature on telecare technologies, this thesis highlights the need for further research to include different patient groups, technologies, and projects design.

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Appendix

Tables from estimates

Main estimates for the expenditures in LTC Services

These are the tables corresponding to the ATT estimates in section 5.1 on the expenditures in LTC services. All the tables show estimates measured in 1000 NOK.

Table 7: Expenditures in long term care services

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	0.35	1.21	-1.99	2.71
1	Average	0.88	2.73	-4.64	6.10
2	Average	1.09	3.37	-5.59	7.65
3	Average	0.45	1.55	-2.70	3.53
4	Average	0.90	2.84	-4.68	6.41
5	Average	-0.11	0.95	-1.87	1.69

Table 8: Expenditures in nursing home services

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	0.01	0.77	-1.55	1.52
1	Average	0.45	1.65	-2.87	3.81
2	Average	0.83	2.75	-4.54	6.40
3	Average	0.45	1.76	-3.09	3.99
4	Average	0.63	2.30	-4.06	5.23
5	Average	-0.32	1.39	-3.11	2.42

Table 9: Expenditures in home based care services

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	0.69	2.12	-3.33	5.05
1	Average	-0.11	0.81	-1.65	1.54
2	Average	-0.36	1.51	-3.20	2.59
3	Average	-0.41	1.58	-3.40	2.66
4	Average	0.37	1.38	-2.22	3.17
5	Average	0.35	1.47	-2.46	3.39

Main estimates for the utilization of LTC services

These are the tables corresponding to ATT the estimates in section 4.2.1 on the utilization of nursing home spaces and home based care services (Section 5.2)

Table 10: Number of nursing home beds per 1000 inhabitants

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	0.02	0.73	-1.40	1.53
1	Average	-0.27	1.12	-2.39	1.93
2	Average	0.05	0.72	-1.36	1.44
3	Average	0.11	0.70	-1.28	1.42
4	Average	-0.54	1.89	-4.19	3.11
5	Average	-0.90	2.92	-6.57	4.77

Table 11: Utilization NH services - Percentage of 80+ population

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	0.37	2.04	-3.76	4.24
1	Average	-0.01	1.80	-3.54	3.43
2	Average	0.06	1.84	-3.47	3.48
3	Average	0.55	2.52	-4.04	5.93
4	Average	-0.97	3.97	-9.18	6.79
5	Average	-1.37	5.08	-11.80	8.37

Table 12: Utilization HBC services - Percentage of 80+ population

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	2.33	7.75	-13.11	16.79
1	Average	0.67	3.35	-6.03	7.09
2	Average	2.18	7.19	-11.81	15.52
3	Average	2.07	6.83	-11.72	15.25
4	Average	3.06	9.77	-15.89	21.62
5	Average	3.47	11.11	-17.83	24.62

Main estimates for the utilization of specialized health services

These tables correspond to the ATT estimates in section 4.2.2 on the utilization of specialized health services for different age groups (Section 5.3). All estimates show the number of admissions as percentages of total number of people in each age group.

Table 13: Hospital admisions - Percentage of 61-70 population

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	0.06	0.17	-0.29	0.40
1	Average	-0.07	0.22	-0.51	0.36
2	Average	-0.08	0.24	-0.54	0.41
3	Average	-0.09	0.29	-0.66	0.47
4	Average	-0.07	0.23	-0.51	0.36
5	Average	-0.07	0.22	-0.49	0.34

Table 14: Hospital admisions - percentage of 71-80 population

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	0.01	0.10	-0.17	0.20
1	Average	-0.21	0.64	-1.42	1.08
2	Average	-0.14	0.44	-0.97	0.72
3	Average	-0.04	0.19	-0.39	0.34
4	Average	0.00	0.12	-0.23	0.23
5	Average	-0.19	0.61	-1.41	1.00

Table 15: Hospital admisions - Percentage of 80+ population

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	-0.02	0.05	-0.11	0.09
1	Average	-0.02	0.07	-0.15	0.12
2	Average	-0.01	0.02	-0.05	0.04
3	Average	0.02	0.08	-0.14	0.17
4	Average	0.00	0.02	-0.05	0.04
5	Average	0.01	0.05	-0.08	0.10

Main estimates for measures of mortality

These tables correspond to the ATT estimates in section 4.3 on measures of mortality per 1000 inhabitants and crude number for different age groups (Section 5.3). Table 15 shows the variation in the number of deaths per 1000 inhabitants. Tables 16 and 17 show the variations in the number of deaths for age specific groups.

Table 16: Variations in number of deaths per 1000 inhabitants

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	-1.19	3.79	-9.28	6.01
1	Average	-0.75	2.46	-6.12	3.75
2	Average	-1.37	4.37	-10.64	6.90
3	Average	0.43	1.67	-2.77	3.77
4	Average	1.51	4.73	-7.77	11.86
5	Average	0.54	1.91	-2.81	4.69

Table 17: Number of deaths - People aged 65-79

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	-1.26	4.18	-9.27	6.90
1	Average	-2.32	7.63	-16.10	12.26
2	Average	-2.34	7.45	-16.51	11.77
3	Average	0.40	3.37	-6.70	6.00
4	Average	0.63	3.20	-5.98	6.86
5	Average	-2.29	7.36	-15.99	12.11

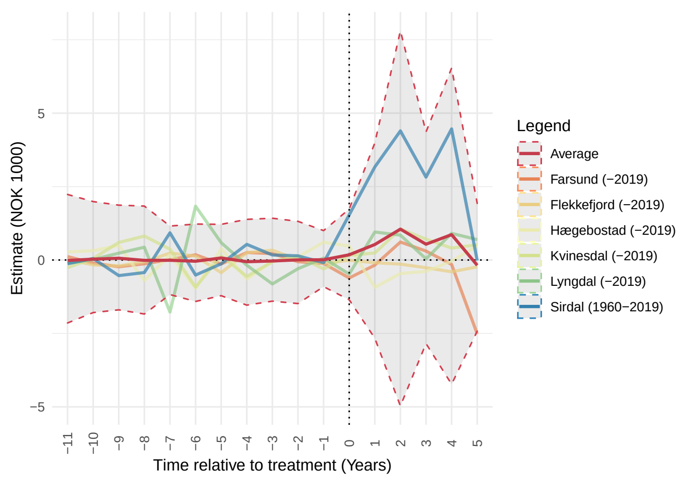
Table 18: Number of deaths - People aged 80+

Time	Level	Estimate	Std.Error	lower_bound	upper_bound
0	Average	-0.96	4.40	-9.54	7.94
1	Average	-2.37	7.59	-17.08	12.09
2	Average	-5.82	18.29	-42.83	29.39
3	Average	2.96	9.48	-15.07	21.27
4	Average	-0.77	3.61	-7.82	6.67
5	Average	0.45	3.12	-5.65	6.83

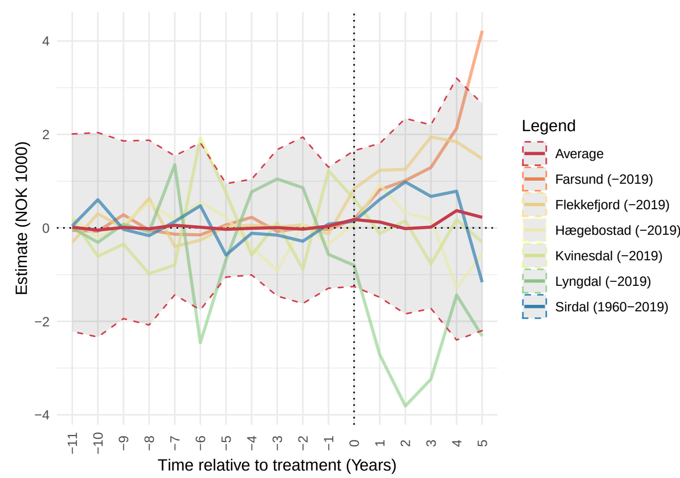
Figures from estimations including auxiliary covariates

Figure 10: ATT Estimation after including auxiliary covariates:

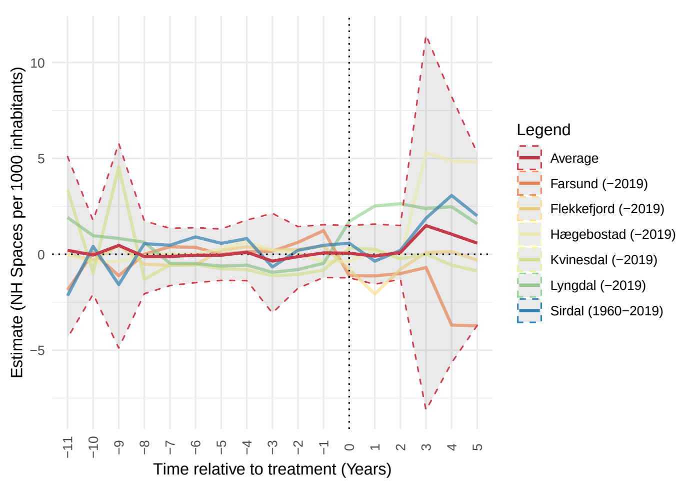
(a) (Real net expenditures in NH services)



(b) (Real net expenditures in HBC)



(c) (Number of beds per 1000 inhabitants)



(d) (Utilization NH - Percentage of 80+ population)

(e) (Utilization HBC - Percentage of 80+ population)