LUND UNIVERSITY
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Does the Swedish specialized health care respond to competition inducing reforms?

- Effects of the Freedom of Choice Act on quality, volume, efficiency and upcoding for elective patients.

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Abstract

This study aims to analyze the effects of competition on quality, efficiency, produced volume and gaming the system of specialized health care in Sweden, after implementation of the Freedom of Choice Act (LOV, Lagen om Vårdval). This is done by using data for specialized ophthalmology, which is a patient-elective diagnostic category. The motive behind the law, which established free entry for private providers and free choice of provider for patients, was to increase competition in the health care sector, increase availability and diversity among health care providers and increase the quality of the health care production. The results of the study show that the volume of produced health care increased in terms of number of hospitalizations and that the quality of care increased in terms of lower rates of unplanned readmissions, after implementation of LOV. The study cannot find any evidence of upcoding patients or that LOV had any effect on efficiency.

Key words: Competition inducing reforms, specialized health care, the Freedom of Choice Act, LOV, Lagen om Vårdval, upcoding, quality, efficiency.

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1. Introduction

In Sweden there is universal access to high-quality health care services on all levels; elderly care, primary care and specialized health care, for all citizens at relatively fair prices. However, health care expenditure has been rising rapidly for decades, waiting times for treatment are long and there is a persistent lack of patient-oriented services (Anell, 2015a). These problems of performance of public health care services has led to discussions about promoting competition in the health care sector, in Sweden and many other countries (Gaynor et al., 2015). The theory behind introducing competition in the health care sector relies on economic models where providers are assumed to maximize profits, hopefully by competing with quality of care in regard to patient satisfaction (Gaynor et al., 2015; Brekke et al., 2014; Dackehag & Ellegård, 2019). The fact that these economic models would apply in sectors whose main objective is not to maximize profits, such as the public health care sector, is however not certain and therefore it is of key policy interest to examine the effects of competition on quality of care.

This study aims to analyze the effects of competition on quality, efficiency, produced volume and gaming the system of specialized health care in Sweden, after implementation of the Freedom of Choice Act (LOV, Lagen om Vårdval). The motive behind the law, which established free entry for private providers and free choice of provider for patients, was to increase competition in the health care sector, increase availability and diversity among health care providers and increase the quality of the health care production (Hälso- och sjukvårdsnämnden, Region Skåne 2013). The law was implemented in 2010 for primary care, and after this date it was optional for counties to also implement it in specialized health care. Four counties in Sweden has up to this date implemented LOV for specialized ophthalmology (eye care). This study will, in contrary to many previous studies, use a patient-elective disease category to test the effect of the competition inducing law. For patient-elective disease categories, the patients can to a high degree can choose their provider of treatment by themselves since treatment is most often not due to an emergency admission, which will better reflect the effect of LOV on patient behavior than acute admissions would. In this setting, providers cannot respond to competition by lowering patient fees, which are regulated by the Swedish health care authority, so the theory is that they have to respond by better quality and efficiency to attract patients (Gaynor et al., 2015; Brekke et al., 2014; Dackehag & Ellegård, 2019).

This raises three key questions on interest:

- Does increased competition in specialized health care prompt providers to improve their quality and efficiency?
- Does competition in specialized health care increase the produced volume of care?
- Does increased competition in specialized health care come with negative effects, such as upcoding patients?

In this study, counties which implemented LOV for specialized ophthalmology will be compared to counties which did not in a difference-in-differences (DID) analysis, on a set of variables which are chosen to measure the effects of competition on specialized health care. The variables of interest are the number of hospitalizations, as well as resource-weighted hospitalizations (DRG-points), number of secondary diagnoses, unplanned readmission rates and hospitals average length of stay for patients undergoing surgery (LOS).

The number of hospitalizations (number of patients visiting a provider) will be used as a measurement of produced volume of health care, hence how good providers are at attracting patients. The resource-weighted hospitalizations (DRG-points) will also be used as a measurement of volume, and the weights represent how resource-demanding a patient's treatment is. The number of secondary diagnoses will be used to examine the effect of competition on providers trying to "game the system". With payment per case providers partly get reimbursed by how complicated a patient's treatment is, in other words how many diagnoses the patient has. Therefore, an increasing number of secondary diagnoses will be an indication of providers giving a patient several unnecessary secondary diagnoses to "upcode" patients as more complicated than they actually are. Unplanned readmission rates will be used as a measure of quality of treatment. Theory says that increased competition among patient-elective treatments should increase quality of care among providers, if prices are regulated. Higher rates of unplanned readmissions are an indication of lower quality of treatment. LOS will be used as a measurement of efficiency of health care in specialized ophthalmology.

In section 2 there will be an institutional background of the Swedish health care sector and competition inducing reforms in Sweden. Related literature will be presented in section 3, and the empirical strategy and data are described in section 4 and 5. The results and robustness test are presented in section 6, section 7 provides a discussion of the results and in section 8 and 9 conclusions and limitations with the study will be presented.

2. Healthcare organization and reform

2.1 Institutional background

Sweden has a decentralized health care system with three political and administrative levels; a central government, 21 county councils and 290 local municipalities. All three levels are involved in financing, providing and evaluating health care services. The 21 independent and locally elected city councils organize the public health care system, except long-term care of the elderly and disabled people (for whom the local municipalities are responsible). In all counties, health care is mainly financed by a proportional income tax, which is complemented by user fees which are determined by the health-care authority. There are both private and public providers operating, and if health care services are provided by a private company under contract with the county council the cost of private and public health care is the same (Socialstyrelsen, 2019).

In Sweden, there is universal access to high quality medical services for all citizens, mostly at reasonable costs (Anell, 2015a). Many evaluations of European health care systems have ranked Sweden among the top countries in terms of patient outcomes and cost efficiency. However, responsiveness to patients and patient satisfaction has been a problem (OECD, 2013). Waiting times for seeing a doctor and receiving treatment, lack of patient-centeredness and that services are not always distributed equally are also persistent problems (Anell, 2015a).

Before the law in question of this paper, other reforms had been implemented to create incentives for providers to attract more patients and produce a higher volume of health care, such as patient-oriented reimbursement schemes (Lindgren, 2014). There are four types of reimbursement models in the Swedish health care system: (1) Grants, reimbursement is a fixed amount given to each provider (a budget), (2) Capitation, the size of the reimbursement is based on size of the population that the provider is responsible for, (3) Payment per case, providers are prospectively reimbursed a fixed sum, depending on the type of case or disease treated, for example by using Diagnosis Related Groupings (DRG) and (4) Fee-For-Service (FFS), a variable system where professionals are retrospectively reimbursed according to an agreed fee-schedule (Lindgren, 2014; Jegers et al., 2002).

In specialized health care in Sweden grants is the most common reimbursement model, used in all counties, but except for a handful of counties it is used in a combination with payment per case and FFS reimbursement models (Lindgren, 2014). Grant reimbursement do not create any incentives to increase the volume of produces health care, it rather creates incentives to cut down on the use of resources as much as possible. The opposite is true for payment per case and FFS reimbursement models, they create incentives to produce as much health care as possible to maximize the retrospective reimbursement (Lindgren, 2014). For the treated counties in this study, all except Jönköping has used DRG-based reimbursement in combination with grants in specialized ophthalmology before the implementation of the law in question in this study. For data of which years, during the sample period, the treated counties in this study used DRG-based reimbursement in outpatient and inpatient care, see appendix A.

2.2 The Freedom of Choice Act

The Swedish government decided in 2010 that other reforms of the health care system was necessary, both to increase competition and to ensure the right for all patients to decide which health care provider they want to visit. In 2010 each individual county council were responsible to implement the Freedom of Choice Act (LOV) in the primary health care sector, and it was voluntary for counties to implement LOV in specialized health care. The purpose of the latter was to increase competition in specialized health care, increase availability among health care providers, increase the power of choice for patients and to increase the quality of the health care production (Hälso- och sjukvårdsnämnden, Region Skåne 2013). By the regulations of LOV, external providers can request to enter the market of specialized health care. Each county council is responsible for the quality of care of both public and external providers, so each county council set up their own requirements of market entry and as long as an external provider fulfill the requirements they cannot be rejected (Hansson, 2014).

The motive behind allowing external providers to enter the specialized health care market is to increase the produced volume of specialized health care, to increase availability and reduce the waiting time, and overall to induce a more patient-oriented health care (Hansson, 2014). Since prices in specialized health care are regulated by the Swedish health care authority the providers cannot attract patients by lowering their fees, but instead they will have to compete by quality (Gaynor et al., 2015; Brekke et al., 2014; Dackehag & Ellegård, 2019).

3. Related literature

The Swedish government introduced the Freedom of Choice Act for specialized health care in 2010, with the motive to increase competition in the health care sector, increase availability and diversity among health care providers and to increase the quality of the health care production (Hälso- och sjukvårdsnämnden, Region Skåne 2013). However, the past literature of the effects of competition on quality and efficiency in the health care sector is ambiguous. In this section the previous literature of the effect of competition in the health care sector on quality, efficiency and undesirable outcomes, such as "gaming the system" by upcoding and cream-skimming, will be presented.

Theoretical models of competition with fixed prices suggests that hospitals should compete by increasing quality of care for diseases with the greatest profitability and demand elasticity (Colla et al., 2016). Colla et al. examined this theory by studying the relationship between competition and quality for what should be the most competitive markets, in this case by using elective hip and knee replacement as a proxy of quality of care, finding no association between the two. Moscelli et al. (2016) also studied the effect of increased competition in the UK health care sector on quality, also for hip and knee replacements, but by using emergency readmissions as a proxy for quality of care. They find that the choice reform increased emergency readmissions and hence, quality of care fell. They mean that these results are in line with theories stating that quality could fall following an increase in competition, if the regulated price is less than the cost of treating additional patients or if the marginal cost of treatment is greater when quality is higher (Mosecelli et al., 2016).

Cooper et al. (2011) studied the effect of competition on hospital quality, using mortality from acute myocardial infarction in the English National Health Service. They find that after the competition inducing reforms were implemented, mortality fell for patients living in more competitive areas. Their results therefore suggest that competition between hospitals can lead to improvements in hospital quality (Cooper et al., 2011). Gaynor et al. (2013) did a similar study, also finding strong evidence that under regulated prices hospitals within the NHS engaged in activities that increased quality of patient care. Within two years of implementation, the reforms resulted in significant improvements in mortality and decreasing length of stay without changes in total expenditure per patient (Gaynor et al., 2013).

Cooper et al. (2012) studied the effect of competition inducing reforms on efficiency in the English NHS, using LOS (hospitals average length of stay for patients undergoing surgery) as a measurement of efficiency, finding that the reforms improved clinical quality. Their results show that competition between public sector hospitals resulted in moderate but statistically significant reductions in pre-surgery, post-surgery and overall LOS (Cooper et al., 2012). Also, they find no evidence that the competition inducing reforms induced hospitals to discharge patients "sicker and quicker", and no evidence that public hospitals tried to avoid treating older and less wealthy patients, so called cream-skimming (Cooper et al., 2012).

Upcoding and cream-skimming are undesirable outcomes from increased competition in the health care sector. Upcoding patients is to classify patients as belonging to a more severe disease category than what is medically warranted in order to receive higher compensation, and cream-skimming is to cut down on expensive patients or to only admit patients classified as easy cases to receive higher compensation (Serdén et al., 2002). Several studies have tried to find evidence of upcoding due to financial incentives in the health care sector. Serdén, Lindqvist and Rosén (2002) did a study regarding upcoding after introduction of DRG-based prospective payment systems in Sweden. They find that all regional hospitals had an increase of the number of coded secondary diagnoses and of the number of secondary diagnoses per patient. However, hospitals with DRG-based reimbursement had a larger increase, starting after the system was introduced. The regional hospitals which did not have DRG-based payments had a more constant increase, which also coincided with the introduction of DRG-based management systems. They conclude that irrespective of use, DRG-based systems focus on registering diagnoses and therefore increases the number of diagnoses, and hospitals without DRG-based reimbursement systems have fewer registered secondary diagnoses than hospitals with DRG-based reimbursement systems (Serdén et al., 2002).

Dackehag and Ellegård (2019) studied the Freedom of Choice Act for the primary health care in Skåne, Sweden, which loosened entry restrictions for both public and private providers and increased patients' freedom of choice, thus increased competition in the primary health care market. They make a distinction between local markets with monopoly power and markets where there are many providers for patients to choose from. They find that public primary care providers react to increased competition from private providers, and that patients received more diagnoses, maybe in an attempt for primary care providers to increase profits, in areas that were affected by higher competition. However, they note that increased diagnoses registrations in competitive areas need not indicate that patients are receiving unnecessary diagnoses, upcoding, because examples were also found where providers under- as well as over-report diagnoses in primary care (Dackehag & Ellegård, 2019). Dietrichson et al. (2016) examined the heterogeneous impact of competition enhancing reforms, also in the Swedish primary care, on patient satisfaction and avoidable hospitalization rates. They found that regions that were more affected by reforms that increased patient choice and reduced barriers to entry experienced small improvements of patients' overall impression of quality of care, but no improvements of avoidable hospitalization rates or waiting times. They conclude that the reforms had limited effect on patients' access to care and hence, that increased competition is the most likely mechanism behind the results (Dietrichson et al., 2016).

One year after implementing the Freedom of Choice Act for specialized health care, a study of the effects of the law on specialized eye- and skin care in Skåne was published (Anell, 2015b). The results show, one year after implementation in Skåne, that the law on average had a positive effect on availability, in terms of number of patients who received treatment. The capacity of health care production was stable, which indicates that higher availability was achieved through improved efficiency. The waiting time for patients to receive health care within specialized eye care had, on average, been shortened in counties with LOV, compared to counties without LOV. By shortening the waiting time for patients, there had also been an increase in the volumes of health care production (Anell, 2015b). Anell uses the amount of DRG-points as an indicator for volume of produced health care, finding that the production of DRG-points in Skåne has increased by 16 % from the first quarter in 2014 to the first quarter in 2015. This increase was partly due to private providers entering the market after LOV, and therefore increasing the health care production in the region. Anell states that this increase could be due to the fact the reimbursement from DRG-points creates incentives to prioritize simple cases of readmissions and hence, that health care providers are involved in gaming the system by upcoding or cream-skimming (Anell, 2015b). However, the results from this study needs to be tested in a deeper analysis, since it only examines a single county over a short period of time, and there is no econometric testing used to compare changes in this single county to changes in counties in the rest of Sweden, which the author himself also stresses.

4. Empirical strategy

In section 4.1 the identification strategy and the robustness test used to test this strategy will be presented. The equations used for estimations will be presented in section 4.2.

4.1 Identification

The three key questions of interest in this paper are:

- Does increased competition in specialized health care prompt providers to improve their quality and efficiency?
- Does competition in specialized health care increase the produced volume of care?
- Does increased competition in specialized health care come with negative effects, such as upcoding patients?

A difference-in-differences analysis will be used, comparing treated counties and control counties. The treatment group consist of the counties that has implemented LOV for specialized ophthalmology during the sample period, which will be separated into two sub-groups: "LOV 2012" where Stockholm is the only treated county, which implemented LOV in 2012, and "LOV 2014" where Uppsala, Jönköping and Skåne are the treated counties which implemented LOV in 2014. Skåne will, in addition to being included in LOV 2014, also be treated separately to compare the results from this study with the Anell (2015b) study. The sub-groups will not be used as each other's control groups. Instead, the control group used for both treated sub-groups consist of the remaining 17 counties in Sweden, which did not implement LOV for specialized ophthalmology during the sample period.

The key identifying assumption for a DID method is that the trends of the dependent variables would be the same in both treated counties and control counties in absence of the reform. If this assumption holds, the treatment effect can be isolated by subtracting the trend in the control counties from the change in the treated counties. This assumption will be tested graphically in section 5.2, by viewing the trend for the dependent variables for both treatment and control counties, before and after implementation of LOV for specialized ophthalmology. Counties with extreme values compared to the rest of the treatment or control group will be excluded from the regressions, separately for each dependent variable. Due to this, the complete treatment and control group will seldom be used in the regressions. A robustness test in the form of a placebo test will also be executed to ensure that the identification strategy is not compromised by other unknown factors, such as earlier policy-interventions.

4.2 Estimation

The following equation will be used for estimations:

$$y_{it} = \alpha + \beta_1 Treated_i + \beta_2 PostLOV_t * Treated_i + \mu_t + \varepsilon_{it} \quad (1)$$

where y_{it} is a vector of dependent variables, $Treated_i$ is a dummy indicating which counties implemented LOV, $PostLOV_t$ is a dummy indicating over which years the law was used for each treated county. β_2, the interaction parameter of $PostLOV_t * Treated_i$, is the parameter of interest. A rejection of the null hypothesis that β_2 equals zero indicates an effect of LOV on quality, efficiency, volume and upcoding in specialized healthcare. Year fixed effects, μ_t, is included and ε_{it} is an idiosyncratic error term. Standard errors are clustered at county-level.

The following equation will be used for the placebo test:

$$\begin{aligned} y_{it} = \alpha + \beta_1 Treated_i + (\beta_2 PostLOV_t + \beta_3 PostLOV_{t-1} + \beta_4 PostLOV_{t-2} \quad (2) \\ + \beta_5 PostLOV_{t-3} + \beta_6 PostLOV_{t-4}) * Treated_i + \mu_t + \varepsilon_{it} \end{aligned}$$

where y_{it}, $Treated_i$ and $PostLOV_t$ are the same as in equation (1). In this specification, "placebo-years" of implementation of LOV are included to see if the identification strategy is compromised by other factors from earlier years. This is done by lagging the year of implementation of LOV by 1-4 years. A rejection of the null hypotheses that β_3, β_4, β_5 and β_6 equals zero indicates an effect of LOV or other unknown factors on quality, efficiency, volume and upcoding from years previous to implementation of LOV. As in equation (1), year fixed effects, μ_t, is included, ε_{it} is an idiosyncratic error term and standard errors are clustered at county-level.

5. Data

In section 5.1 the dependent variables will be explained, and summary statistics and descriptive statistics for the two treated sub-groups will be presented. In section 5.2 the assumption of parallel trends will be tested graphically.

5.1 Data

The Freedom of Choice Act for specialized ophthalmology was implemented in Stockholm in 2012, and in Skåne, Uppsala and Jönköping in 2014 (Valfrihetswebben, 2012; Valfrihetswebben, 2014; Anell, 2015b). Until today, these four counties are the only ones with the Freedom of Choice Act for specialized eye care. The information about provided ophthalmological services (eye treatment for diseases in the eyes and nearby organs) derives from the national patient register from Socialstyrelsen, containing information about number of hospitalizations and DRG-points for each patient treated at a hospital in Sweden with a main diagnosis in the Major Diagnostic Category 2, number of secondary diagnoses, unplanned readmission rates and average length of stay for hospitalized patients (LOS, number of bed-days for each hospitalized patient divided by the number of hospitalizations). In the data set, both public and private health care providers are included, for both inpatient and outpatient care.

Specialized ophthalmology is a category of illnesses where patients can choose provider for themselves since it is most often not an emergency treatment, therefore competition can be examined for this specific category of illnesses. The logarithm of the number of hospitalizations (number of patients visiting a provider) will be used as a measurement of produced volume of health care, hence how good providers are at attracting patients. The logarithm of the resource-weighted hospitalizations (DRG-points) will also be used as a measurement of volume, and the weights represent how resource-demanding a patient's treatment is. The logarithm of the number of secondary diagnoses will be used to examine the effect of competition on upcoding patients, so an increasing number of secondary diagnoses will be an indication of upcoding patients. Unplanned readmission rates will be used as a measure of quality of treatment., in particular higher rates of unplanned readmissions are an indication of lower quality of treatment. LOS (hospitals average length of stay for patients undergoing surgery) will be used as a measurement of efficiency of health care in specialized ophthalmology.

Table 5.1: Summary statistics for control group and treatment group (before trimming).

Variables	Control group					Treatment Group				
	Obs.	**Mean**	**Std. Deviation**	**Min.**	**Max.**	**Obs.**	**Mean**	**Std. Deviation**	**Min.**	**Max.**
Log Hospitalizations	221	9.991	1.052	3.714	11.929	52	11.288	0.901	9.742	12.996
Log DRG-points	220	6.473	0.719	4.813	8.894	52	7.744	0.768	6.411	9.044
Log Secondary Diagnoses	221	9.371	1.006	3.526	11.318	52	10.561	0.890	8.522	12.095
LOS	221	3.071	0.959	1.417	7.843	52	3.672	1.196	1.830	7.230
Unplanned Readmission Rates	221	8.338	5.494	1.291	32.662	52	6.468	3.827	0.545	17.605

The summary statistics for all variables during the years 2005-2017, separated for complete control group and complete treatment group, can be seen in table 1. In total, the treated counties consist of 52 observations over four counties, and the control group consist of 221 observations over 17 counties. On average, the treatment group has more hospitalizations, DRG-points and secondary diagnoses than the control group. The average length of stay for hospitalized patients, LOS, is longer in the treatment group than in the control group, and the treatment group has a lower rate of unplanned readmissions. The two variables LOS and Unplanned Readmission Rates are not logarithmic since the former is a product of two variables (the number of days hospitalized divided by the number of hospitalizations) and the latter is a rate going from 0 to 100.

In table 5.2 and 5.3 below, descriptive statistics can be seen for the two treated sub-groups. “LOV 2012/14” indicates the counties that implemented LOV in 2012/14. “PreLOV” indicates the years before LOV was implemented and “PostLOV” indicates the years after it was implemented. The statistical difference between the treatment and control group for both periods, PreLOV and PostLOV, and all dependent variables are tested with a t-test. These tables will also give an indication of the change in the treated sub-groups over the sample period, to see if there is a difference in means for all dependent variables before and after implementation of LOV.

Table 5.2: Descriptive statistics for LOV 2012 (before trimming).

Variables	**LOV 2012 PreLOV** n=7		**Control PreLOV** n=227		**t-test between groups PreLOV**	**LOV 2012 PostLOV** n=6		**Control PostLOV** n=228		**t-test between groups PostLOV**
	Mean	SD	Mean	SD	p-value	Mean	SD	Mean	SD	p-value
Log Hospitalizations	11.932	0.275	10.067	1.138	0.0000	12.895	0.147	10.050	1.090	0.0000
Log DRG-points	8.478	0.249	6.532	0.795	0.0000	8.702	0.173	6.535	0.789	0.0000
Log Secondary Diagnoses	10.556	0.383	9.432	1.060	0.0001	11.678	0.292	9.407	1.013	0.0000
LOS	6.056	0.855	3.091	0.961	0.0001	3.830	0.808	3.163	1.085	0.1003
Unplanned Readmission Rates	3.813	0.905	8.218	5.472	0.0000	3.800	1.065	8.200	5.467	0.0000

In table 5.2, the descriptive statistics for the treated sub-group LOV 2012 can be seen. It can be seen that the average number of Hospitalizations, amount of DRG-points and number of Secondary Diagnoses has increased from before implementation of LOV until after implementation of LOV, and that LOS and Unplanned Readmission Rates has decreased. There is a significant difference between the treated county and the control counties for all dependent variables both before and after LOV, except for the variable LOS in period PostLOV.

Table 5.3: Descriptive statistics for LOV 2014 (before trimming).

Variables	**LOV 2014 PreLOV** n=35		**Control PreLOV** n=225		**t-test between groups PreLOV**	**LOV 2014 PostLOV** n=30		**Control PostLOV** n=230		**t-test between groups PostLOV**
	Mean	SD	Mean	SD	p-value	Mean	SD	Mean	SD	p-value
Log Hospitalizations	10.827	0.640	10.023	1.070	0.0000	10.687	0.578	10.058	1.085	0.0000
Log DRG-points	7.385	0.663	6.504	0.747	0.0000	7.267	0.642	6.538	0.775	0.0000
Log Secondary Diagnoses	10.273	0.872	9.407	1.0326	0.0000	10.119	0.831	9.446	1.056	0.0002
LOS	3.225	0.688	3.073	0.953	0.2564	3.159	0.712	3.085	0.947	0.6095
Unplanned Readmission Rates	6.949	3.905	8.383	5.471	0.0622	7.172	4.171	8.323	5.427	0.1784

The descriptive statistics for the treated sub-group LOV 2014 can be seen in table 5.3. This subgroup has the opposite trend as the sub-group LOV 2012. Hence, the average number of Hospitalizations, amount of DRG-points, number of Secondary Diagnoses and LOS has decreased from before implementation of LOV to after implementation, and Unplanned Readmission Rates has increased. For most dependent variables there is a significant difference between the treated counties and the control counties, both before and after LOV, except for the variables LOS and Unplanned Readmission Rates.

Since the two treated sub-groups have opposite trends for the development of the means before and after LOV they will be tested separately when running the regressions.

5.2 Assumption of parallel trends

The key identifying assumption of parallel trends for a DID method will be tested graphically by viewing the trend for the dependent variables for both treatment and control counties, before and after implementation of LOV for specialized ophthalmology.

The observations for the dependent variables were first plotted separately for all counties, identifying which counties that are outliers in the data set. From this plot, counties with observations that are identified as outliers or extreme values are excluded from the data set, for each dependent variable separately. Below, graphs for the dependent variables can be seen, indicating that the assumption of parallel trends is fulfilled after trimming the data set. Stockholm is graphed separately since LOV was implemented in 2012, and Uppsala, Jönköping and Skåne are graphed together as one treatment group, for which LOV was implemented in 2014. In addition, Skåne is also graphed separated from the other two counties that implemented LOV in 2012. Note that Stockholm is not included in the control group for LOV 2014 and Uppsala, Jönköping and Skåne are not included in the control group for LOV 2012.

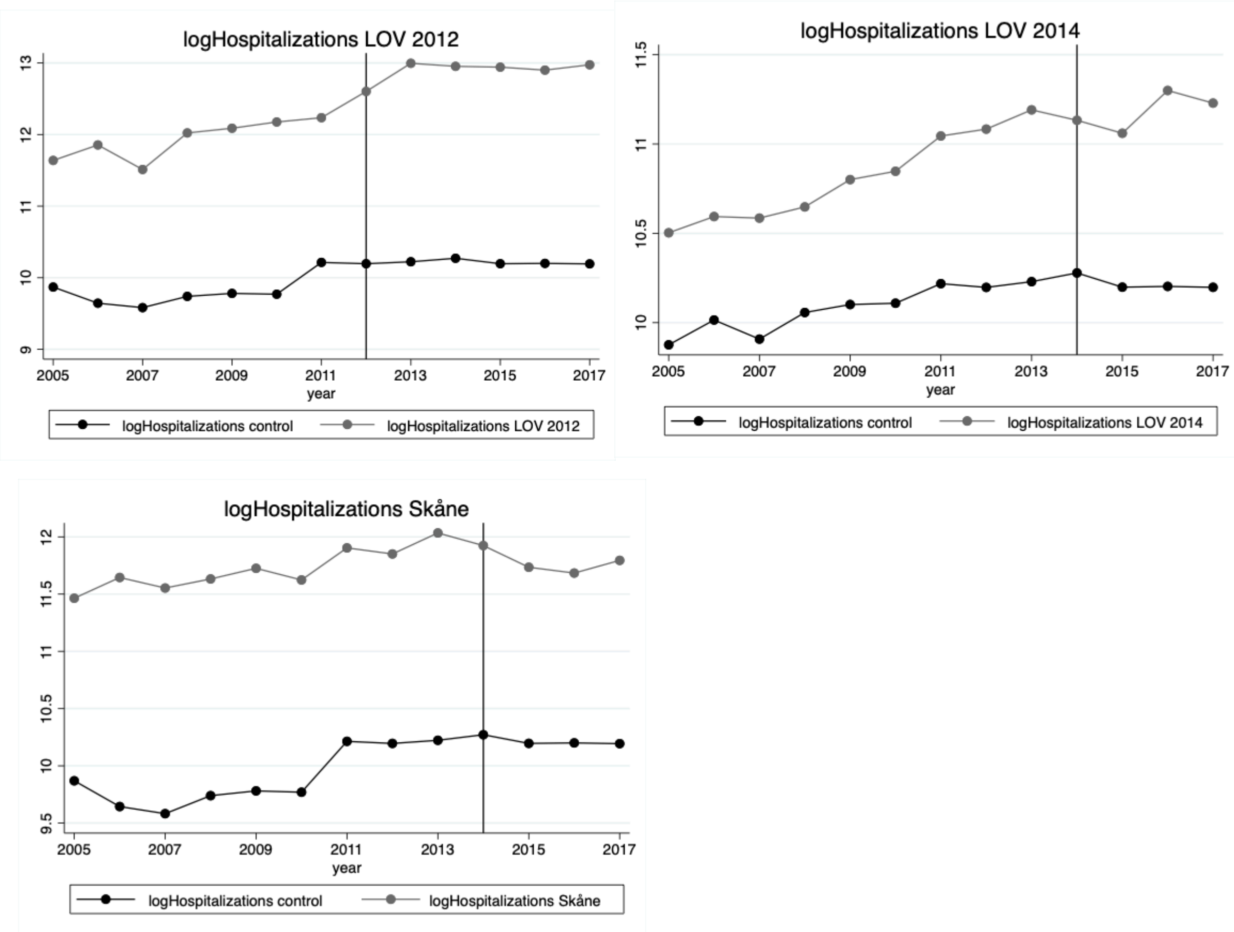
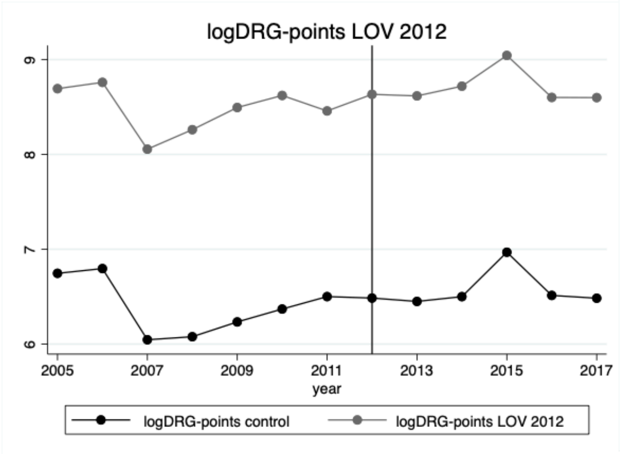
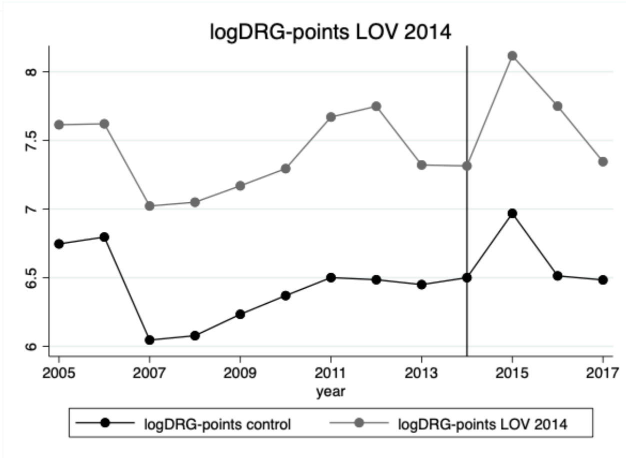


Figure 5.1-5.3: The logarithm of the average number of Hospitalizations for LOV 2012 (Stockholm), LOV 2014, Skåne separately and control group.

In figure 5.1, the trends for logHospitalizations for LOV 2012 can be seen. Stockholm is the treated county and all control counties are included. In figure 5.2 the trends can be seen for LOV 2014, where Uppsala, Jönköping and Skåne are treated counties. Kronoberg has been excluded from the control group due to extreme values compared to the rest of the control group. In figure 5.3 the trends can be seen for Skåne separated from the other counties in LOV 2014, all control counties are included.





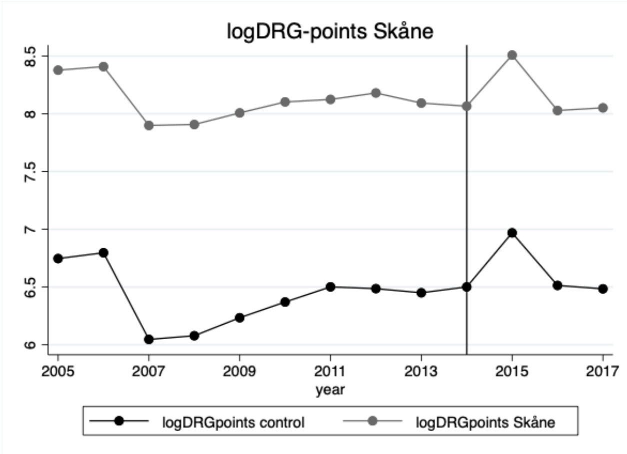


Figure 5.4-5.6. The logarithm of the average DRG-points for LOV 2012, LOV 2014, Skåne separately and control group.

In figure 5.4 the trends for logDRG-points for LOV 2012 can be seen. Stockholm is the treated county, and all control counties are included. In figure 5.5 the trends for logDRG-points for LOV 2014 and control group can be seen. Uppsala has been dropped from the treatment group due to extreme values compared to the control group. All counties in the control group are included. In figure 5.6 the trends can be seen for Skåne, separated from the other counties in LOV 2014. All control counties are included.

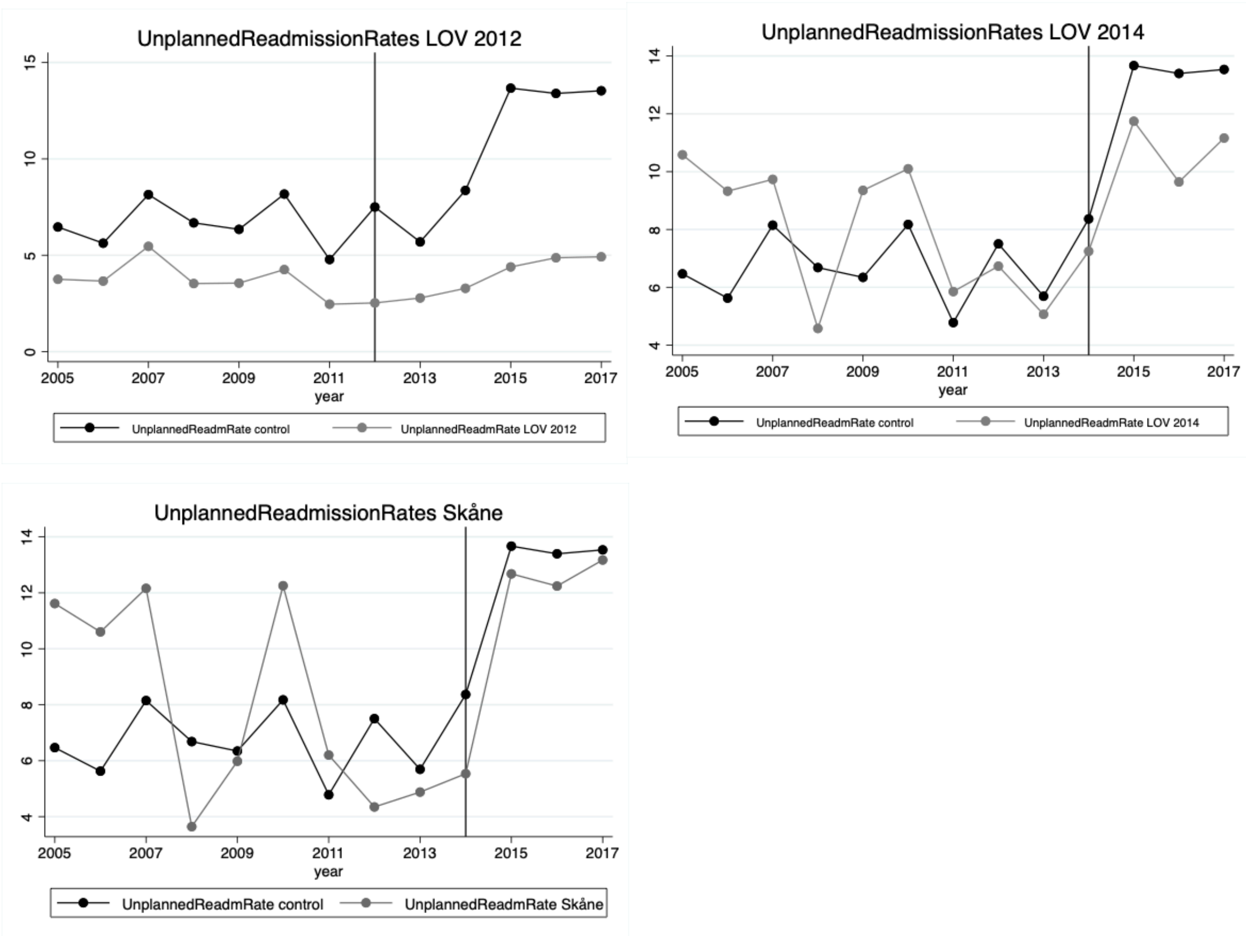


Figure 5.7-5.9: Average Unplanned Readmission Rates for LOV 2012, LOV 2014, Skåne separately and control group.

In figure 5.7 and 5.8 the trends for treated and control group can be seen for the variable Unplanned Readmission Rates. No county has been excluded from the control group in either LOV 2012 or LOV 2014, but Uppsala has been excluded from the treatment group for LOV 2014 due to extreme values compared to control group. In figure 5.9 the trends for Skåne, separated from the other treated counties in LOV 2014, can be seen. All control counties are included.

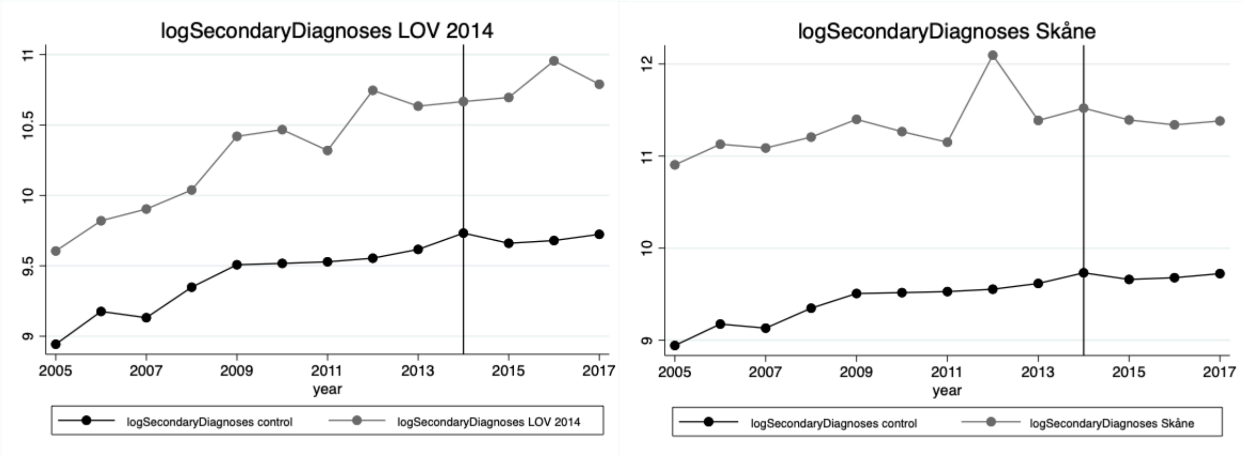


Figure 5.10 and 5.11: The logarithm of the average number of Secondary Diagnoses for LOV 2014 (Jönköping, Uppsala and Skåne), Skåne separately and control group.

In figure 5.10 and 5.11 the trends for the variable logSecondaryDiagnoses for LOV 2014 and Skåne, separated from the other treated counties in LOV 2014, can be seen. Kronoberg has been dropped from the control group for both LOV 2014 and Skåne separately, due to extreme values compared to the rest of the control counties. Stockholm has been dropped from the treatment group so there will be no regression for this variable for LOV 2012.

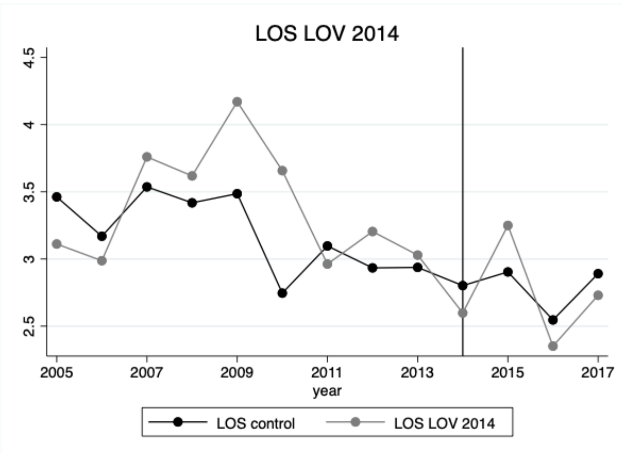


Figure 5.8: Average length of stay (LOS) for LOV 2014 (Jönköping) and control group.

In figure 5.8 the trends for the variable average length of stay for hospitalized patients (LOS) can be seen for LOV 2014 and control group. All treated counties except for Jönköping has been excluded due to extreme values compared to the control group. All control counties are included. Stockholm was dropped from the treatment group for LOV 2012, and since it is the only treated county included in that group no regression will be performed for this variable for

LOV 2012. Skåne was dropped from the treatment group for LOV 2014, and therefore no regression for this county separately will be performed.

Summing up, the regressions will be performed with these trimmed data sets for each dependent variable in section 6. A summary of the excluded counties can be seen in table 5.4.

Table 5.4: Summary of the trimmed data sets for each dependent variable and for both treated sub-groups LOV 2012 and LOV 2014, and Skåne separately.

LOV 2012		
Variables	**Excluded treated counties**	**Excluded control counties**
logHospitalizations	-	-
logDRG-points	-	-
Unplanned Readmission Rates	-	-
logSecondary Diagnoses	Stockholm (no regression)	(no regression)
LOS	Stockholm (no regression)	(no regression)
LOV 2014		
Variables	**Excluded treated counties**	**Excluded control counties**
logHospitalizations	-	Kronoberg
logDRG-points	Uppsala	-
Unplanned Readmission Rates	Uppsala	-
logSecondary Diagnoses	-	Kronoberg
LOS	Uppsala Skåne	-
Skåne		
Variables	**Excluded treated counties**	**Excluded control counties**
logHospitalizations	-	-
logDRG-points	-	-
Unplanned Readmission Rates	-	-
logSecondary Diagnoses	-	Kronoberg
LOS	Skåne (no regression)	(no regression)

6. Results

In this section the results from the main regressions and the robustness test will be presented. The results of robustness test in section 6.2 will be discussed lightly in this section, and in section 7 the results from the main regressions and what implications the robustness test means for them will be discussed thoroughly.

6.1 Main results

Table 6.1: Regression results for treated sub-groups, Skåne and dependent variables.

VARIABLES	(1) logHospitalizations	(2) logDRG-points	(3) UnplannedReadmRate	(4) logSecondaryDiagnoses	(5) LOS
LOV 2012					
Treated	2.133***	2.082***	-2.791***		
	(0.289)	(0.173)	(0.538)		
PostLOV*Treated	0.549**	0.053	-3.772***		
	(0.246)	(0.033)	(0.870)		
Constant	9.849***	6.739***	6.472***		
	(0.160)	(0.177)	(0.872)		
Observations	234	233	234		
R-squared	0.274	0.411	0.326		
LOV 2014					
Treated	0.732*	0.979**	1.323**	0.848	0.191
	(0.422)	(0.383)	(0.524)	(0.531)	(0.120)
PostLOV*Treated	0.229	0.036	-3.614**	0.230	-0.244
	(0.143)	(0.107)	(1.341)	(0.206)	(0.140)
Constant	9.859***	6.730***	6.761***	8.914***	3.432***
	(0.167)	(0.175)	(0.861)	(0.166)	(0.276)
Observations	247	259	247	247	234
R-squared	0.224	0.304	0.304	0.292	0.110
Skåne					
Treated	1.824***	1.710***	1.362**	1.923***	
	(0.245)	(0.171)	(0.525)	(0.166)	
PostLOV*Treated	-0.255	-0.164***	-2.696**	-0.213***	
	(0.192)	(0.030)	(1.155)	(0.065)	
Constant	9.857***	6.742***	6.678***	8.945***	
	(0.158)	(0.177)	(0.896)	(0.167)	
Observations	234	233	234	221	
R-squared	0.182	0.328	0.309	0.390	
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. In the first group, LOV 2012, Stockholm is the only treated county included and in the second group, LOV 2014, Jönköping, Uppsala and Skåne are the treated counties included. In the third group, Skåne is separated from the other treated counties in LOV 2014. Remember, in some regressions counties from both treatment and control group has been excluded due to extreme values (see section 5.2).

The regression results for all dependent variables and treated groups can be seen in table 6.1. In column 1, the regression results for the logarithm of the number of hospitalizations can be seen. There is small significance in the first treated group ($p<0.05$) for the interaction variable, PostLOV*Treated, and the point estimate of 0.549 indicate a positive effect of LOV on produced volume of health care. Stockholm, therefore, on average attracts 5.6 % more patients after implementation of LOV, relative to the mean of all counties during the sample period. For LOV 2014 there is no significance, but the point estimate of the interaction variable is also positive and the magnitude of the effect of LOV on produced volume of health care is half as big. For Skåne separately, the interaction variable is not significant, but the point estimate indicates a negative effect of LOV on produced volume of health care. In column 2, the regression results for the logarithm of the number of DRG-points can be seen. There is no significance in the interaction variable for any of the two sub-groups. The point estimates are positive and varies from 0.036 to 0.053, indicating that the effect of LOV for this measurement of produced volume of health care is also positive. However, for Skåne separately the interaction variable is significant ($p<0.01$) and negative, indicating that logDRG-points decreased by 2.4 %, relative to mean of all counties during the sample period.

In column 3, the regression results for share of Unplanned Readmission Rates can be seen. The interaction variable is significant in both treated sub-groups and for Skåne separately ($p<0.01$-0.05) and the point estimates varies between -3.772 and -2.696, indicating that LOV improves this measurement of quality of care by 40.4-58.3 %, relative to the mean of all counties during the years 2005-2017. In column 4, the regression results for the logarithm of the number of Secondary Diagnoses can be seen. The interaction variable is not significant for LOV 2014, but the point estimate indicates a positive effect of LOV on number of secondary diagnoses. For Skåne separately the interaction variable is significant ($p<0.01$) and the point estimate of -0.213 indicates that the secondary diagnoses decreased by 2.4 %, relative to the mean of all counties during the sample period. The regression results for average length of care for hospitalized patients, LOS, can be seen in column 5. There is no significance, but the negative point estimate indicates a positive effect of LOV on efficiency.

6.2 Robustness test

Table 6.2: Placebo test for LOV 2012, LOV 2014 and Skåne separately.

VARIABLES	(1) logHospitalizations	(2) logDRG-points	(3) UnplannedReadmRate	(4) logSecondaryDiagnoses	(5) LOS
LOV 2012					
Treated	1.970***	1.973***	-2.454***		
	(0.289)	(0.179)	(0.748)		
$PostLOV_t$*Treated	0.711***	0.162***	-4.108***		
	(0.245)	(0.046)	(1.173)		
$PostLOV_{t-1}$*Treated	0.052	-0.016	0.136		
	(0.246)	(0.071)	(0.958)		
$PostLOV_{t-2}$*Treated	0.436***	0.278***	-1.462		
	(0.120)	(0.057)	(1.183)		
$PostLOV_{t-3}$*Treated	0.337***	0.287***	-0.336		
	(0.102)	(0.049)	(0.919)		
$PostLOV_{t-4}$*Treated	0.313***	0.210***	-0.694		
	(0.093)	(0.039)	(1.127)		
Constant	9.858***	6.745***	6.453***		
	(0.160)	(0.179)	(0.892)		
Observations	234	233	234		
R-squared	0.275	0.412	0.326		
LOV 2014					
Treated	0.635	0.916**	2.061***	0.736	0.115
	(0.465)	(0.409)	(0.596)	(0.593)	(0.198)
$PostLOV_t$*Treated	0.326*	0.099	-4.352***	0.342	-0.169
	(0.173)	(0.172)	(1.381)	(0.258)	(0.198)
$PostLOV_{t-1}$*Treated	0.327	-0.044	-2.686***	0.281	-0.024
	(0.214)	(0.062)	(0.804)	(0.216)	(0.399)
$PostLOV_{t-2}$*Treated	0.251	0.348	-2.832	0.456***	0.156
	(0.221)	(0.311)	(2.426)	(0.123)	(0.323)
$PostLOV_{t-3}$*Treated	0.192	0.254	-0.988	0.054	-0.250
	(0.264)	(0.321)	(0.774)	(0.201)	(0.188)
$PostLOV_{t-4}$*Treated	0.104	0.009	-0.136	0.214	0.796***
	(0.144)	(0.046)	(1.865)	(0.223)	(0.210)
Constant	9.875***	6.739***	6.684***	8.931***	3.436***
	(0.167)	(0.178)	(0.867)	(0.167)	(0.284)
Observations	247	259	247	247	234
R-squared	0.226	0.306	0.307	0.295	0.113
Skåne					
Treated	1.881***	1.740***	2.146***	1.924***	
	(0.318)	(0.179)	(0.594)	(0.166)	
$PostLOV_t$*Treated	-0.312	-0.193***	-3.480**	-0.214**	
	(0.278)	(0.040)	(1.218)	(0.088)	
$PostLOV_{t-1}$*Treated	-0.070	-0.097**	-2.960***	-0.153	
	(0.276)	(0.044)	(0.780)	(0.091)	
$PostLOV_{t-2}$*Treated	-0.226	-0.045	-5.303***	0.617***	
	(0.280)	(0.044)	(1.557)	(0.090)	
$PostLOV_{t-3}$*Treated	-0.191	-0.117	-0.726	-0.302***	

	(0.278)	(0.068)	(0.751)	(0.061)	
PostLOV_{t-4}*Treated	-0.027	-0.007	1.933*	-0.175**	
	(0.082)	(0.044)	(1.023)	(0.062)	
Constant	9.853***	6.740***	6.634***	8.945***	
	(0.161)	(0.179)	(0.900)	(0.170)	
Observations	234	233	234	221	
R-squared	0.183	0.328	0.314	0.393	
Year FE	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Four leads (lags of 1-4 years from the implementation year of LOV) have been included for all dependent variables. LOV was implemented in 2012 for the first group, so the leads are regarding the years 2008-2011. LOV was implemented in 2014 for the second group, so the leads are regarding the years 2010-2013.

The placebo test for LOV 2012, LOV 2014 and Skåne separately can be seen in table 6.2. In column 1 and 2, the placebo test for logHospitalizations and logDRG-points can be seen. Despite the promising pre-trend graphs in section 5.2, the placebo tests for these two measurements of volume show systematic placebo-effects for LOV 2012. For hospitalizations (column 1), the point estimate of the main interaction variable, PostLOV_t*Treated, is higher than the placebo-point estimates, indicating that there was a greater effect of LOV when the law was actually implemented, than in the placebo-implementation years. For resource-weighted hospitalizations (column 2), the point estimates of the placebo-effects for LOV 2012 are higher than the point estimate for the main interaction variable. Since there was no significance for this variable in the main regression these results are not surprising. The significance of the leads could partly be due to anticipatory effects, that the health care market prepared for LOV before the actual implementation. However, it is most probably the case that the main regressions are not only picking up the effect of LOV, but also other reforms or changes in the specialized health care sector. For LOV 2014 and Skåne separately, there are no systematic placebo-effects. The point estimates of the interaction variables for both dependent variables are similar to the point estimates in the main regression, indicating somewhat robust results.

In column 3, the placebo test for UnplannedReadmissionRates can be seen, showing no significance and small point estimates for all leads for LOV 2012. In the main regression, the point estimate of the interaction variable was -3.772 and, in the placebo test it is -4.108, indicating that the main results are robust. For LOV 2014 there is no systematic placebo-effect for this variable. The interaction variable for UnplannedReadmissionRates is significant and similar to the point estimate of the main regression, indicating robust results. For Skåne separately, there are significant placebo-effects 2 years prior to implementation year, and the absolute values of point estimates in the placebo test are larger than in the main regression. The significant leads for LOV 2014 and Skåne could partly be due to anticipatory effects, but also that the main regression is not only picking up the effect of LOV. In column 4 and 5, the placebo tests for logSecondaryDiagnoses and LOS can be seen. For LOV 2014, they do not show any systematic placebo effect. The interaction variables in the main regressions for both variables are similar to the ones in the placebo tests, indicating somewhat robust results. For Skåne separately, there is a systematic placebo effect for logSecondaryDiagnoses and the point estimates of the significant placebo-years are larger than the ones in the main regression, indicating that the results from the main regression are not robust.

7. Discussion

For the treated sub-group LOV 2012 (Stockholm), the effects of implementing LOV were analyzed on three variables: logHospitalizations, logDRG-points and Unplanned Readmission Rates. The regression results show a significant effect of LOV on one of the measurements of produced volume of health care, number of hospitalizations, which increased by 5.6 % in Stockholm, relative to mean of all counties during the sample period. However, the placebo test indicates that it is not solely the effect of LOV that is captured in the main regression, since there is a systematic placebo-effect for this variable. It is probably the case that the effect captured in the main regression is due to a mix of policy interventions rather than only the implementation of LOV, for example the use of patient-oriented reimbursement schemes like Fee-for-Service or DRG-based payments per case.

When using the resource-weighted measurement of volume for Stockholm, DRG-points, there is no longer a significant effect of LOV and the point estimate is significantly smaller, but still positive. There is a systematic placebo-effect for this measurement of volume as well, indicating that this study cannot isolate an effect of LOV on resource-weighted produced volume. Even though, comparing the size of the point estimates of the two measurements of volume, it indicates that the casemix in Stockholm after implementing LOV consists of slightly more complicated cases (diagnoses and necessary treatments of patients) than in the control group, but that the increase in produced volume mostly derives from treating more patients rather than more complicated patients.

The last variable for sub-group LOV 2012, Unplanned Readmission Rate, show a significant and relatively big effect of LOV on this measurement of quality of care in Stockholm, where the rate fell by 58.3 %, relative to the mean of all counties during the sample period. However, the trend-analysis in figure 5.7 in section 5.2 indicates that this result is not due to a strong decrease in unplanned readmissions in Stockholm, but rather a strong increase for the control group. It could be that the implementation of LOV was what caused the unplanned readmissions to remain rather stable while the control group had a strong increase, which is also consistent with the results of the placebo test since there is no indication of systematic effects from earlier policy-interventions.

For the treated sub-group LOV 2014 the effects of implementing LOV was analyzed on five variables: logHospitalizations, logDRG-points, Unplanned Readmission Rates, logSecondaryDiagnoses and LOS. There was no significance for either of the two measurements of produced volume, which is not very surprising when looking back at the trend-analysis in figure 5.2 and 5.5 in section 5.2 since the treated counties and the control counties have similar trends, both before and after implementation of LOV. The effect of LOV on quality of care, Unplanned Readmission Rates, for LOV 2014 is similar to the effect for LOV 2012, significant and negative, with a decrease of unplanned readmissions by 53.5 %. However, looking back at figure 5.8 in section 5.2 it can be seen that the trend differs from the trend of LOV 2012 for this variable. Both treated and control counties had a strong increase in unplanned readmissions during one year before and one year after implementation of LOV, but for the treated sub-group there was a decrease in unplanned readmissions for the treated counties in 2016, while the control group remained stable. There was no evidence of a systematic placebo-effect, so the significant decrease seems robust.

The results from this study cannot show any proof of providers upcoding patients due to increased competition for LOV 2014. The point estimate of the number of secondary diagnoses is insignificant, but robust and positive which could indicate some upcoding, but far from validate it. For Skåne separately the result from the main regression, though not robust due to systematic placebo-effects, instead indicate a decrease in number of secondary diagnoses. In the study by Anell (2015b) he found an increase in DRG-points one year after implementation of LOV in Skåne. He states that this increase could be due to the fact the reimbursement from DRG-points creates incentives to prioritize simple cases of readmissions and hence, that health care providers are involved in gaming the system by upcoding or cream-skimming (Anell, 2015b). In Skåne, reimbursement from DRG-points were stopped in 2012, prior to implementation of LOV. This could partly explain the decrease in DRG-points found in this study and hence, the decrease in number of secondary diagnoses. Lastly, there is no significant effect of average length of stay for hospitalized patients, LOS. Although, the point estimate is robust and negative, which could indicate that patients are hospitalized for a shorter period of time and hence, that hospitals in counties with LOV has increased their efficiency slightly.

The related literature in section 3 had found contradictory effects on quality of care after introduction of competition: everything from negative effects, to no effect, to positive effects. The majority of the literature presented on this subject are using emergency readmissions or mortality rates from acute myocardial infarctions as their measurement for quality (Moscelli et al., 2016; Cooper et al., 2011; Gaynor et al., 2013). For acute diagnoses and emergency readmissions the patients themselves cannot choose which provider to visit. If they are picked up by an ambulance, they will get transported to a hospital that has enough capacity to admit them, or the nearest placed hospital from where the patient lives. Instead, Colla et al. (2016) and this study have used patient-elective treatments to be able to capture the behavioral response of patients from competition, which should therefore be the best measurement for isolating the effects on quality from competition inducing reforms. This study finds a positive relationship between competition and quality of care, where unplanned readmission rates in specialized ophthalmology decreased significantly after implementation of LOV.

The related literature had also found that LOV increased the volume of produced healthcare in specialized ophthalmology in Skåne, one year after implementation, due to the entry of private providers in the health care sector (Anell, 2015b). This study finds opposite results, that the number of hospitalizations and DRG-points decreased in Skåne after implementation of LOV. The method in the study by Anell (2015b) was to analyze the effect in one single county during one single year, while this study compared the development in Skåne to the development in 17 control counties. In the study by Anell, it is therefore impossible to know if a change in a variable actually is an effect of LOV or just an average change in the entire country due to other factors. The results from this study therefore seems more probable to capture the actual effect of competition on produced volume. Also, Anell stated that while the produced volume increased, the capacity was at the same time stable. Therefore, the increased volume was most likely achieved through higher efficiency, which could not be tested for Skåne separately in this study.

8. Conclusion

The purpose of this paper was to analyze three key questions. First, if increased competition in specialized health care prompted providers to improve their quality and efficiency. Second, if competition in specialized health care increased the produced volume of care. Third, if increased competition in specialized health care came with negative effects, such as upcoding patients.

This study found some evidence of increased produced volume of health care due to increased competition, but only in Stockholm, and the results are not robust to the actual implementation year of LOV. For Skåne separately, the results instead indicate a decrease in produced volume due to increased competition. This study also found a significant and relatively big effect on the measurement of quality of care, where unplanned readmission rates decreased by 40.4-58.3 % in some of the counties that implemented LOV, relative to the mean of all counties during the sample period. Theory states that sectors with no incentives to maximize profits, such as public hospitals, would need to respond to increased competition by increased quality and patient-satisfaction, which the results from this study can validate. The study cannot find any evidence of providers upcoding patients, instead the opposite effect was found in Skåne separately. Lastly, the study cannot find any effect of competition on efficiency in specialized health care.

The purpose of implementing The Freedom of Choice Act for specialized health care was to increase competition in specialized health care, increase availability among health care providers, increase the power of choice for patients and to increase the quality of the health care production. The intuition behind this partly relied on economic models about maximizing profit-behavior which not necessarily applies in the public health care sector. Therefore, the importance of evaluating the effects of this law in the public health care sector cannot be stressed enough. Hopefully, this study as well as past studies can shed light on some evidence regarding the Freedom of Choice Act in specialized health care and help policy makers with future policy interventions.

9. Limitations

There are some limitations to this study that could be taken into account for future research. Firstly, this study only used data for one category of specialized health care, and for this particular MDC there where only four counties that implemented LOV during the sample period. Using one or several other MDCs might balance the treatment and control group to a higher extent, increasing the probability of isolating the effect of LOV. Second, the robustness test indicated that the main regression caught other effects than the effect of LOV, making the choice of model questionable. Since the treated counties implemented LOV during different years another model might have been able to isolate the effect of LOV to a greater extent, for example a fixed-effects model. Third, it would have been useful to include data on the number of new providers in each county after the implementation of LOV. There might still be a lot of competition between existing providers but if not, and if there were actually no new providers after implementation of LOV, this could bias the results. Lastly, many of the variables used in this study are self-reported by each hospital and county, making them somewhat less reliable. For example, as seen in section 5.2, the county Kronoberg had to be excluded from the control group in several regressions due to extreme values, which could be caused by mistakes such as double registering.

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Appendix

Appendix A

Table A1: Counties using DRG-based reimbursement in outpatient care.

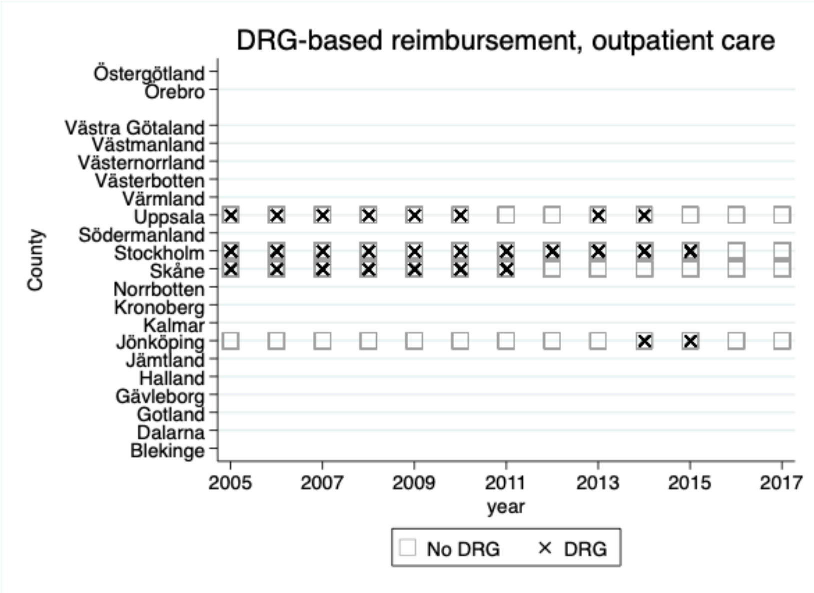

Table A2: Counties using DRG-based reimbursement in inpatient care.