UiT The Arctic University of Norway

School of Business and Economics

# Financial incentives in Norwegian somatic hospitals

## An early look at how hospitals respond to the profit incentive in Norway

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# Preface

This thesis marks the conclusion of my master's degree in Business administration at the School of Business and Economics at UiT The Arctic University of Norway.

I would like to thank my supervisor Helen Marita Sørensen Holst and other helpful staff members for guidance through the process of making this thesis.

Through the writing of this thesis, I have been able to explore healthcare funding and the sometimes-sharp contrast between the responsibilities of the state as our collective insurer and the financial incentives of providers to standardize treatments and specialize outputs. I have also had the opportunity to explore variety of methods in stochastic frontier analysis, bayesian estimation and multilevel modeling. As well as experienced the data and computational limitations of complex model and estimation methods that can follow.

I would like to thank my family for all the support throughout this process. A special thanks to my incredible partner Christina and son Henrik, who have been my most important source of motivation during this period.

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# Abstract

**Background***:* The cost brought about by healthcare systems in western society is high and likely to increase in the future. Governments with activity-based funding (ABF) systems attempt to increase efficiency by introducing financial incentives, using internal market mechanisms for hospitals under the umbrella of new public management. The prospective payment system in Norway nudges hospitals into becoming quantity-adjusting market participants, by adding self-adjusting prices to diagnostic groups based on national averages. Hospitals then compete for financial surplus and thus the ability to fund future investments.
**Problem***:* The Norwegian government has utilized activity-based funding (ABF) for over 20 years and the effect of the profit incentive innate to the system is still not fully understood. This means that hospital decision-makers may be using illegitimate strategies to increase profitability. New data that allows analysis of profit incentives at the diagnosis-related group (DRG) level became available in 2017, and no analysis of financial incentives including this cost information has yet to be published.
**Method**: An iterative approach to achieve a parsimonious crossed multilevel model design to isolate the effect of profit from other financial incentives for somatic hospitals in Norway. This was done using the R-package *lme4.* The data included price, cost, and quantity data from 18 hospitals between 2018 and 2021.
**Results***:* The results show that there is a small association between the average profit of a DRG and number of admissions. With a semi-elasticity for the population effect of 3.21% for admissions per 1 unit increase in average DRG profit.
**Conclusion***:* This thesis shows how analyzing profit in a divided funding healthcare system is possible given a few assumptions of the mechanisms in the funding systems. The results indicate that there is an association between the profit incentive and admissions of a DRG. The model should be considered robust to the deviations in model assumptions of residual normality and variance. Future research including either more years of analysis or a different model is still needed to confirm the effect of profit and the impact of including patient characteristics in the analysis.



Keywords: ISF, DRG, KPP, Norwegian somatic hospitals, Profit incentive.

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# Abbreviations

| **Abbreviation** | **Explanation** |
|---|---|
| KPP | Cost-per-patient |
| ABF | Activity-based funding |
| DRG | Diagnosis-related group |
| RHF | Regional Health Trusts |
| HF | Health Trust |
| MLM | Multilevel model |
| ML | Maximum likelihood |

# 1 Introduction

Norwegian healthcare spending per capita was reported as the fourth highest among OECD-countries in 2016 when adjusted for purchasing power. Amounting to 10.5% of gross domestic product, only surpassed by the US, Switzerland, and Luxembourg (Vold, 2017). Like many others, the Norwegian healthcare system has been put through several reforms with the aim to reduce cost and increase productivity (Hagen & Kaarbøe, 2006). One of the reforms was the introduction of an activity-based funding system (ABF). Aimed at increasing efficiency and control to ensure timely access to healthcare services for the population, in accordance with the waiting list guarantee introduced in 1990. (Meld. St. 44, 1995-1996)

ABF is a prospected payment system based on differentiating funding between groups of diagnoses. In an economic context these diagnosis related groups (DRG) can be thought of as the products of hospitals where each have their own price, reflecting the resources needed for treatment of patients within the group (Januleviciute et al., 2016). The DRG system was developed by Fetter and Thompson at Yale University in the 1970s and implemented for the first time in the US in 1983. Since then, the DRG and ABF systems have been adopted to different degrees by policymakers in the US, UK, China, as well as several European countries (Palmer et al., 2014).

Miraldo, Goddard and Smith (2006) shows that the aims of ABF implementation in the UK, was increased efficiency, reduced waiting lists, better allocation of resources and improved development, among others. They also state that "... *there is potential for prospective payment systems to create perverse incentives and encourage unwanted behaviours from providers"* (Miraldo et al., 2006, p. 13) and that there may be shifts in available services that hospitals provide, and which patients are treated.

Complex financial healthcare systems are prone to gaming practices (Lægreid et al., 2015). Several strategies can be applied to increase reimbursements legitimately or illegitimately. Ellis (1998) on page 538 defines 3 illegitimate strategies as *"'creaming', the over-provision of services to low cost patients, 'skimping', the under-provision of services to high cost patients, and 'dumping', the explicit avoidance of high cost patients."* A later definition used by Martinussen and Hagen (2009, p. 139) define a similar strategic concept of cream skimming as *"…the selective treatment of patients that demand few resources while providing high economic refunds"* and can occur both within and between DRGs. Another

similar strategy is upcoding, defined by Simborg (1981) referenced in Anthun et al. (2016) on page 84 as *"a deliberate and systematic shift in a hospital's reported case mix in order to improve reimbursement"*.

In publicly owned healthcare systems, the demand for services tend to exceed supply (Januleviciute et al., 2016). Because of the excess demand, the influence of economic incentives on the provision of services does not necessarily mean that hospitals undermine their duties. Providing the population with an increased volume of services within the hospitals budget constraints may increase the amount of "health" being produced. As mentioned previously, this is one of the main reasons for implementing ABF in the first place. Understanding the effect of economic incentives in ABF on treatment volumes is therefore vital to evaluating the effects of ABF implementations.

The lion's share of literature on financial incentives of hospitals are based on price and price changes. In Norway, some research has been done on the subject (Januleviciute et al, 2016; Melberg et al., 2016; Anthun et al., 2016). A Taiwanese study by Liang (2015) examined the own-price elasticity of profit. They tried to overcome the lack of cost data by using inpatient fees as a proxy on a small sample of DRGs. See section 2.3 and 2.4 for a short review of the selected studies. However, little or no research has been done at a high level on the effect of profit on DRG admissions. As indicated by both Martinussen and Hagen (2009) and Januleviciute et al, (2016), the information required for a high-level analysis of *between* DRG skimming effects was unavailable to them at the time. Due to new data collection requirements from the national health authorities, such data now exists.

Norwegian regional health authorities and hospitals have been tasked with collecting cost data connected to DRGs in the cost-per-patient (KPP) management system since 2018 (Ministry of Health and Care Services, 2017) The KPP system ties both direct and indirect accounting information to activities connected to each individual patient treatment. The development of the KPP system is a natural extension of the implementation of ABF and has been in development since 2005 (Sandvik et al., 2006: p. 2).

The data collected through the KPP system provides hospitals with information that can be acted upon to become more cost-efficient in areas where they are below national averages. In situations where increased cost-efficiency seems infeasible, managers or physicians may

attempt to utilize the different strategies defined by Ellis (1998) or attempt to increase profitability within the funding system in other ways.

## 1.1 Research questions

It seems clear, given the newly available data, that an analysis that includes cost data to expand on the price-based analysis of previous research is necessary. Leading to the subject of this thesis. *Do Norwegian somatic hospitals respond to profit incentives?*

This subject can be analyzed from different perspectives, among them looking at the three strategies formulated by Ellis (1998) and through upcoding. However, the scope of this thesis will be limited to a profit-based analysis of cream skimming *between* DRGs and effects on DRG admissions. Using the definition of cream skimming by Martinussen and Hagen (2009). This can be operationalized with the following main research question (RQ) below.

> *RQ 1: "Is there an association between the number of admissions and the profit incentive of DRGs in the Norwegian somatic hospitals, when controlling for price, patient and time effects?"*

In other words, does the financial incentive of profit affect the number of admissions in a systemic way in Norway? This is not certain. Hospital organizations are complex and includes internal allocation rules (Januleviciute et al. 2016). This means that many other factors, both financial and otherwise, may influence decisions regarding the number of patients treated within a DRG, other than the profit margin.

An economic model of the utility function of hospital decision-making is described by Biørn et al. (2003). The utility function, naturally, includes other elements than the profit incentive. Which leads to the second research question:

> *RQ 2: "How elastic are DRG admissions to changes in profit?"*

This will be answered by calculating the elasticity of admissions to changes in profit relative to the level of profit from the DRG.

Most of the factors that impact admission decisions can probably not be accounted for in this analysis, but data on price, patient and time has been collected for this analysis. This means that both systemic budget effects and exogenous price and patient shocks are removed from

the profit effect, leaving the hospital's own profit-increasing and admission-adaptation efforts in focus since the implementation of KPP.

The first controlled variable is price, which should have negative association between number of treatments and the resource intensity of the DRG reflected by the DRG-weight. Previous research found changes in the DRG-weights to be associated with changes in admissions to a small degree. This effect can occur because of widely applied technological changes or other possible cost inflationary changes like described in Januleviciute et al. (2016).

The composition of patients within a DRG for each year may impact the number of admissions and costs associated with treatment. The collected variables include averages of age, gender, and length of stay, based on elements of the analysis in Anthun et al. (2016). The last included aspect that may affect the number of admissions is time. The data from 2018 to 2019 includes the years of 2020 and 2021, in which most aspects of Norwegian society were impacted by restrictions to decrease the spread of the covid-19 pandemic.

The analysis is based on a multilevel model using the maximum likelihood estimator (ML). To generalize any results from RQ 1 and 2, the assumptions for multilevel modeling and maximum likelihood estimator need to be adequately satisfied. This will be tested using visual residual analysis.

## 1.2 Structure of the thesis

Chapter 1 has introduced the financial incentives in the Norwegian ABF system and previous research on the subject. It also identified gaps in the literature and defined two key aspects in RQ 1 and 2 that has the capacity to add to the current understanding of the subject. The remainder of this thesis is structured as follows.

Chapter 2 provides an understanding of the financial context of the Norwegian healthcare funding system, previous studies on similar topics and the elasticity of admissions with regards to profit.

Chapter 3 describes the theory on multilevel modeling and its application in maximum likelihood estimation.

Chapter 4 describes the data, model and applied methods.

Chapter 5 presents results from the selected model, elasticity calculation and residual analysis.

Chapter 6 includes a discussion of the results in light of available theory.

Chapter 7 offers concluding remarks on the findings, limitations, and future research.

# 2 Activity-based funding in Norway

This chapter describes the fixed and activity-based parts of the funding system, the relationship between them and uses available literature to assemble a theoretical framework for examining the profit incentive. This is achieved by interpreting the Norwegian ABF system as an artificial internal market as defined by Le Grand (1991) and defining hospital reactions to price and profit incentives as described by Januleviciute et al (2016) and Biørn et al. (2003) respectively. The approach of both papers is inspired by Chalkley and Malcomson (1998).

## 2.1 Reforms and fixed funding

In 1997 and 2002 respectively, the financial system and ownership of Norwegian somatic hospitals were reorganized to increase efficiency, scope of hospital care, and adapt to activity-based financing (ABF) systems in other western countries such as the UK in the early 1990s. (Biørn, et al., 2003; Hagen & Kaarbøe, 2006)

The responsibility of supplying an adequate degree of health services and allocating funding between hospitals was then divided between 5 regional health authorities (RHF) which were later reduced to 4 in 2007. The hospitals within the 4 regions are organized into health trusts (HF), some of which may include several units in different geographical locations (Braut, 2022).

The responsibility to ensure health care services includes requirements about availability, quality, cost efficiency and adapted to the needs of the patients. The main purpose of the funding system is to contribute to the fulfillment of the requirements (Ministry of Health and Care Services, 2015). The funding system as a whole is complex and include several different subsystems. The ABF system includes in addition to DRGs, special service groups, while they function similarly to DRG, that cover different aspects of treatment (Norwegian Directorate of Health, 2019).

The funding of RHFs is divided into two parts. The first portion is fixed, and the second is activity based. These parts are divided to contribute equally to the financing of RHF and distributed autonomously between hospitals. The fixed funding is updated yearly, and the

model has been adjusted two times by the Magnussen-committee in 2008 and 2019 (Ministry of Health and Care Services, 2021) The fixed funding is designed to account for differences in gender, age, health, social and geographic aspects which may differ between hospital regions. With an overall goal to deliver equal financial conditions to the RHFs, and therefore more equal quality of health services to the population on an aggregate level (NOU2019:24, p. 42)

## 2.2 ABF as a quasi-market

In the funding and ownership transitions, the state went from being both the provider and insurer of specialist healthcare services through its counties to primarily acting as the insurer. Creating a quasi-market for the provision of somatic healthcare services (Le Grand, 1991). According to Le Grand (1991), quasi-markets, also known as internal markets, differ from free markets in several ways.

The quasi-market is achieved by introducing market imitating mechanisms (Chalkley & Malcomson, 1998). In contrast to retrospective reimbursement, with ABF, hospitals cannot set prices and are incentivized to reduce costs (Biørn et al., 2003). In the Norwegian context, the quasi-market consists of not-for-profit public organizations and for-profit organizations that compete for public contracts and customers.

In Norway between 2018 and 2021, patients could freely decide which of preapproved hospital organization to be referred to ("fritt behandlingsvalg", 2015, § 2-4). This introduces competition for demand. Chalkley & Malcomson, (1998) on p. 2 state that patient demand is a *"natural economic mechanism for maintaining quality"* and that *"If patients are free to choose where to go for treatment, their choices will reflect their perceptions of the quality of services on offer, even if they do not themselves pay directly for those services."*

## 2.3 Price incentives in ABF

Within ABF the treatment of patients is divided into relatively homogenous DRG product categories (Eastaugh, 1999). Each patient is assigned a DRG based on a DRG-algorithm. Revenue in monetary terms from each patient treated in the DRG is calculated in the following way according to Januleviciute et al. (2016)

$$p_{it} = g_{it} z_t M_t \tag{1}$$

Where $p_{it}$ is the price for treatment of patients in DRG *i* in year *t*, $g_{it}$ is the cost-weighting for DRG *i* in year *t*, $z_t$ is the funding share of ABF for year *t* and $M_t$ is the national average

treatment cost (NATC) used for patients in year *t*. The first element $g_{it}$ is a result of averaging the treatment cost of patients within each DRG *i* for all hospitals based on historical data. The second element is the politically determined impact of the ABF-share in percent of total RHF revenue. The ABF-share is constant throughout the years of analysis at 50%. The last element NATC $M_t$ is calculated from historical data from 2 years before year *t* (Januleviciute et al. 2016).

Chalkley and Malcomson (1998) as referenced in Januleviciute et al, (2016) states that increased prices within a prospective payment system gives an incentive to increase the number of admissions. Norwegian hospital's reaction to price incentives has been analyzed in previous studies and documented over time through the three studies mentioned here, spanning 10 years of ABF in Norway.

The first study by Januleviciute et al. (2016) examined the association between price and number of admissions within DRGs in Norway between 2003 and 2007. They found a small effect of price on admissions. They report an overall price elasticity of 0.042% and 0.08-0.13% for medical DRGs using fixed-effects models for all DRGs while controlling for time, hospital and DRG fixed-effects. They found no effect for surgical DRGs.

A second study on price changes by Melberg et al., (2016), compared the mean increase of treatments for DRGs between 2006 and 2013 with increasing and decreasing price of different treatment type and diagnostic subgroups. They found a significant difference between the increasing and decreasing price groups who had a 3.16% and 0.74% increase in admissions respectively.

The studies show that hospitals may react to changes in price (Januleviciute et al, 2016), possibly by allocating more resources towards DRGs with increasing prices over time (Melberg et al., 2016). The DRGs with a relatively higher admissions growth may potentially be more profitable than others for some hospitals. However, these results, though they seem to indicate some form of reaction to economic incentives are not transferable to the profit incentive.

Other studies have examined upcoding, where according to the definition of Anthun et al. (2016) patients are merely coded to a complicated, higher paying, DRG than necessary to increase the profitability of treatment. For these studies, the actual costs of treatment for the upcoded patient remain unaffected, while the price difference is the potential gain from

upcoding. This approach is more closely related to the profit incentive because costs are equal for the potentially upcoded patient. Anthun et al. (2016) used a multi-level model on data for the period of 1999 to 2008 and found that 1 DRG-point difference in price between complicated and uncomplicated DRG pairs was associated with a 14.2 percentage point increase in complicated discharges for the un-/complicated DRG pair. For a 1 DRG-point change in the price difference was 0.4% and not significantly different from 0. Januleviciute et al., (2016) also analyzed upcoding, and found that a 10% increase in price-ratio complicated-uncomplicated DRG pairs increased the proportion of complicated patients by 0.3-0.4 percentage points.

## 2.4 Profit incentives in ABF

The theoretical framework of how hospitals can maximize profit in the Norwegian funding system is not well elaborated in the literature because of the missing data required for analysis. However, the mechanisms can be described by using the available information from the studies by Januleviciute et al. (2016), Biørn et al. (2003) and Liang (2015).

Biørn, et al. (2003) defines the profit incentive as a part of hospitals utility function in equation 2.

$$\pi = B + w(e_2) - c(n, e_1) - g \qquad (2)$$

Where the profit $\pi$ is given as the sum of the fixed revenue $B$ and the difference between the marginal revenue $\mathrm{w}(e_2)$ and cost elements $c(n, e_1)$ and $g$. Where $c(n, e_1)$ is the marginal cost and $g$ is a cost component for geographical location and age of the hospital buildings. The marginal revenue is a function of the hospitals coding efforts $e_2$ and the marginal cost is a function of the number of treatments $n$ and level of effort in cost reduction or efficiency $e_1$ (Biørn et al. 2003). They include in this definition the assumptions of increasing revenue with higher coding efforts and a positive and non-decreasing marginal cost.

Hospitals may be able to increase profit in the short run by adjusting admissions of DRGs based on their profitability. The hospitals responsiveness to the profit incentive would depend on internal bargaining between managers and health professionals (Biørn et al. 2003). A hospital would not be able to simply increase the output of profitable DRGs. In the Norwegian context, the number of admissions is limited by the fixed budget, which acts as a maximum treatment limit for each DRG as shown in equation 3 (NOU 2003:1 p. 269). Equation 3 comes naturally as the sum of DRG-points accumulated from the revenue

elements in equation 2 from treated patients given constant coding efforts and the 50% ABF share.

$$\sum_{i=1}^{i} g_{it} y_{it} = B_t \tag{3}$$

Where $g_{it}$ is the DRG-weight and $y_{it}$ is the number of admissions for DRG *i* in year *t*. $B_t$ is the portion of the fixed funding that is available to cover the missing 50% that are not covered under ABF in year *t* in DRG-points.

The first element is the revenue per admission $g_{it}$ in a DRG. The DRG-weight $g_{it}$ is updated yearly based on averaged historical cost data from all hospitals that treat patients in the DRG. In the short term, DRG-weights for the years *t* and *t+1* is available to hospital decision-makers. The second element is number of admissions, of which hospitals are assumed to have some influence. And the limiting factor is the fixed budget.

If a hospital does not have adequate activity to match their fixed funding with ABF funding, then they do not provide the health services necessary to fulfill their responsibility of meeting the modeled healthcare needs of the population it serves. If a hospital's ABF funding exceeds their fixed funding, then they will only be compensated with the ABF-share of the revenue for the volume of treatment above the fixed budget.

According to the utility function Biørn et al. (2003), profit maximizing hospital must attempt to optimize their activity to fit the two requirements placed on them of fiscal responsibility and provision of services. The implication for the analysis of the profit incentive in this thesis is that hospitals are unable to deviate from this admissions goal and therefore can be assumed to operate with a 100% ABF share. The increase in admissions of a profitable DRG would over time have to be accompanied by an admissions reduction with equal reduction in DRG-points as the increase.

Hospitals are then able to optimize the profit from treatment by adjusting the number of admissions of each DRG in response to the known quantities of price, cost, and budget share of the subsequent years. This admissions adjustment is then separate from price changes, efficiency and cost reduction efforts by the hospital and aligns well with the definition of cream skimming that Martinussen and Hagen (2009) used for the selection effect *within* DRG.

Liang (2015) also assumes that hospitals will act on the profit incentive when the information on the difference between price and cost is known. They approach the subject of the profit incentive by building on the framework of Hodgkin and McGuire (1994) and research by Dranove (1987), among others. Dranove (1987) as cited in Liang (2015) on page 455 claims that *"hospitals will expand supply in Medicare DRGs for which they enjoy the largest price–cost margins"*.

The study by Liang (2015) examines the profitability own-price and cross-price effects of competing and complementary surgical DRGs in Taiwan. Analyzing changes in DRG treatment volume with changes in DRG profitability using inpatient fees as a proxy for costs with a small sample of 54 surgical DRGs. They found positive own-price effects when a DRG becomes more profitable, negative cross-price effects when DRGs are substitutes and positive cross-price effects when DRGs are complementary due to economies of scope. Indicating a degree of treatment specialization to profitable DRGs when an estimate of profitability was possible.

## 2.5 Elasticity of admissions to profit

The elasticity is calculated to estimate to what degree hospitals react to the profit incentive by increasing or decreasing DRG admissions. Using the log-linear regression form in Hill, Griffiths and Lim (2018), the elasticity $E_{ij}$ of a DRG *i* within a hospital *j*, is given as

$$E_{ij} = \frac{\frac{\Delta y}{y}}{\frac{\Delta \pi}{\pi}} = \frac{\Delta y}{\Delta \pi}\frac{\pi}{y} = b\pi \tag{4}$$

Where $\pi$ and $\Delta\pi$ are respectively the profit and change in profit, $y$ and $\Delta y$ number of admissions and change in admissions. The elasticity for DRG *i* in hospital *j* is equal to the product of the slope of the profit coefficient $b$ and $\pi$. This form gives the relationship where the constant $b$ is the semi-elasticity, meaning a percent increase in y with a unit increase in $\pi$, and the elasticity increases with the absolute value of $\pi$.

# 3 Multilevel models

This chapter will review the theory of multilevel models and application with maximum likelihood estimation. This includes, firstly, data characteristics indicative of using multilevel models, the assumptions of the model and how to apply the model to time-series data.

Secondly, how to balance type-I and type-II errors in the model specification and how to interpret the implications of deviations from the model assumptions with the maximum likelihood estimator.

MLM, often called mixed-effects model or hierarchical model, are often used in social sciences, and uses hierarchical random effect structures for analyzing data with innate hierarchical properties. MLM separates the variance into distinct levels or groups (Leyland & Groenewegen, 2020). Nalborczyk et al., (2019) on page 1227 define multilevel models (MLM) as a regression model where the parameters are the outcomes of another regression model with hyperparameters at the second level.

Good examples of this kind of structure can be students within classes within schools or firms within industries within countries and other situations where observations share characteristics or traits and therefore may not be independent of each other (Creemers et al., 2010, chapter 11). Maas and Hox (2004) state on page 128 that *"Standard multivariate models are not appropriate for the analysis of such hierarchical systems, even if the analysis includes only variables at the lowest (individual) level".*

## 3.1 Clustering in regression models

Demidenko (2013) on page 3 and 4 say that classical statistics uses the assumption that the data is collected from independent and homogenous individuals and that the residuals have constant variance and a mean of 0. When these assumptions are broken, and the data is clustered in groups, inferences may become very different between models that account for clustering and hierarchical structures in the data or not, as illustrated in figure 1.

In MLMs each group can have their own hyperparameters, for instance the slope and intercept, that can be expressed in the form of the group level equation (Maas & Hox, 2004b).

$$\alpha_{0i} = \alpha_{00} + u_{0i} \tag{5}$$

Where the intercept $\alpha_i$ for group *i* is the sum of the grand mean $\alpha_0$ and the deviation of the group mean from the grand mean $u_{0i}$ with the assumption that $u_{0i} \sim N(0, \tau_{00}^2)$.

In figure 1 below the DRGs may differ in several ways. Compared to the no clustering model on the left, and the group specific intercepts and coefficients in the subject clustering on the

right give a very different understanding of the effect of the effect of profit (DRGP) on admissions (lnAdm).

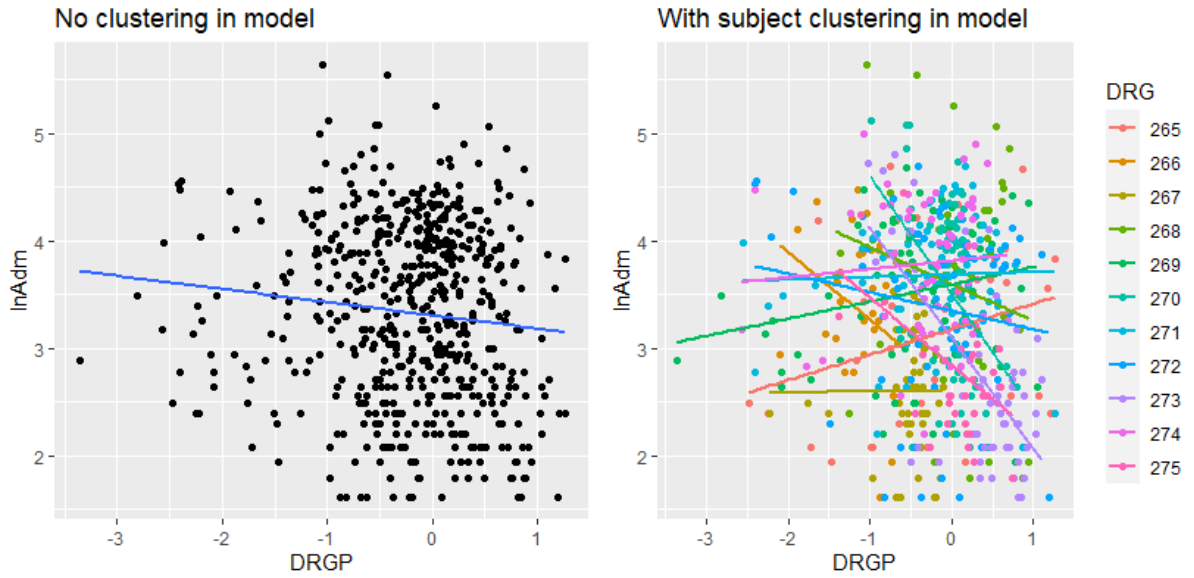


*Figure 1 Differences between assumptions of observational independence*

The amount of variance described by the hierarchical structure is represented by the intraclass correlation (ICC), which expresses the variance explained at the group level in percentage of the total variance of the errors in the null model (Maas & Hox, 2004). The ICC calculated in equation 5, given a model of the variance structure like equation 4, where $y_{ij}$ is the response variable, $\alpha_{00}$ is the grand mean, $u_{0j}$ is the deviation of group *j* from the grand mean and $\varepsilon_{ij}$ is the deviation of the observations from the group mean.

$$y_{ij} = \alpha_{00} + u_{0j} + \varepsilon_{ij} \tag{6}$$

$$ICC = \frac{\tau_{00}^2}{(\tau_{00}^2 + \sigma_\varepsilon^2)} \tag{7}$$

The ICC is the quotient of the of the group variance $\tau_{00}^2$ of the deviations $u_{0j}$ and the total variance $(\tau_{00}^2 + \sigma_\varepsilon^2)$. Described by the group variance $\tau_{00}^2$ and the individual variance $\sigma_e^2$ for the deviations in $\varepsilon_{ij}$. Ignoring the presence of a multilevel structure can increase type I errors even at ICC levels of as low as 0.01 according to Huang (2018).

MLM has clear advantages when it comes to observing the effects of predictors across different levels of the data, but they come at a cost of increased complexity. The variability in

the parameter estimates of the MLM design can be compared to a random sample design by the design effect statistic. Kish (1965) on page 258 as referenced in Lai and Kwok (2015) on page 424 defined the design effect as *"the ratio of the actual variance of a sample to the variance of a simple random sample of the same number of elements"* This statistic expresses the variance inflation that would occur if an assumption of random sampling was used on the data and can be calculated in multilevel models from the ICC and the average cluster size c (Lai & Kwok, 2015).

$$deff = 1 + (c - 1)ICC \tag{8}$$

The design effect can be used to evaluate the need for a multilevel model structure in certain scenarios with a generally accepted threshold value of 2, but this threshold should be used with caution (Huang, 2018).

## 3.2 Assumptions in multilevel models

Multilevel regression assumes, like multiple ordinary least square regression, a linear relationship between dependent and independent variables, no multicollinearity, homoscedastic and normally distributed residuals, and a large enough sample size. (Maas & Hox, 2004b). MLM also assumes normality and homogenous variance within groups (Huang et al., 2022).

The relationship between the variance terms is more complicated in MLM than in classical multivariate regressions. Residuals can be divided into marginal and conditional residuals. The error terms of the group level equations with two error terms or more should have a multivariate normal distribution, be homogenous across groups within levels and be independent from the individual level error term.

$$\binom{u_{0j}}{u_{1j}} = N\begin{pmatrix} 0 & \tau_{00}^2 & \tau_{01} \\ 0' & \tau_{01} & \tau_{00}^2 \end{pmatrix}, \tag{9}$$

In the example of equation 7, $u_{0j}$ and $u_{1j}$ are the group deviations from the grand mean and $\tau_{00}^2$and $\tau_{01}$ are the variance and covariance terms between them. If the variance is not normally distributed and independent, then inference from significance tests in the random structure can be untrustworthy even with large samples (Huang et. al. 2022; Maas & Hox, 2004b).

## 3.3 Multilevel models with longitudinal data

When MLM is applied to panel data it is important to account for both the cross-sectional and time-series aspects of the data. For instance when a test is administered on multiple occasions for students in a classroom. Shor et al. (2007) tested multiple models using Monte Carlo simulations found that for cross-sectional time-series data, MLM is substantially more efficient than ordinary least-squared and fixed effects estimators and can compensate for limited data within groups by partial pooling. They also say that MLM should be better than OLS estimators for wide panels with fewer observations over time. To account for contemporaneous correlation *between* subjects at time *t*, the parameter $\gamma_t$ is added to vary in the time dimension (Shor et al., 2007).

Shor et. al. (2007) presented a random intercept and fixed slope two-level model

$$y_{jt} = \alpha_j + \gamma_t + \beta x_{jt} + \varepsilon_{jt} \tag{10}$$

$$\alpha_j = \alpha_0 + u_j \tag{11}$$

To achieve the multilevel form, equation 11 is substituted in equation 10, giving the multilevel model in equation 12.

$$y_{jt} = (\alpha_0 + u_j) + \gamma_t + \beta x_{jt} + \varepsilon_{jt} \tag{12}$$

Where $y_{jt}$ is the dependent variable for subjects *j* in time *t*. The intercept $\alpha_j$ is the sum of the hyperparameters $\alpha_0$ and $u_j$, and $\alpha_j + \gamma_t$ are respective initial states for subjects *j* and time *t*. $\beta x_{jt}$ is the coefficient and varying predictor for subjects and time and $\varepsilon_{jt}$ is the error term for subjects *j* at time *t*. In the level two equation $\alpha_j$ is defined as the deviation $u_j$ of the subject from the grand mean initial state $\alpha_0$ and the error term is normally distributed $u_j \sim N(0, \sigma_u^2)$.

## 3.4 Design and model selection

Barr et al. (2013) argue that for confirmatory hypothesis testing researchers should "Keep it maximal". Stating on page 257 that *"Failure to include maximal random-effect structures … inflates Type I error rates."*. They argue against data driven model-selection because of the number of decisions involved and lack of guidelines in specifying the correct random-effect structure can cause anti-conservativity in inferences.

In studies where the researcher wishes to test a hypothesis regarding a fixed effect, Bates et al. (2015) recommends a procedure to increase parsimony in the model. On page 3, they say that the optimization problem in maximum likelihood estimation increases with the complexity of the model. This is because of the large number of variance and covariance parameters estimated in the random effects structure and when too complex for the information present in the data it can be constrained in complicated ways. This according to them, leads to overparameterized models that can have harmful consequences for inferences. They also state on page 4 that

> *"The primary reason for dealing with the random-effects structure is to obtain as powerful tests as justified of the fixed effects ... Therefore, it is reasonable to remove variance components/correlation parameters from the model if they are not supported by the data."*

The procedure proposed by Bates et al. (2015) is as follows. First, to check the number of dimensions supported by the data with principal component analysis (PCA) and secondly, attempt to reduce the dimensionality of the variance-covariance matrices for random effects by removing higher-order interaction effects. Thirdly, test if forcing zero-correlation between parameters reduces the goodness of fit according to the log-likelihood ratio test (LRT), Akaike information criterion (AIC) and Bayes information criterion (BIC). Fourth, taking out variance components one by one while checking for a significant reduction in goodness of fit. Fifth, adding in correlation components after removing terms from the model in step four. And sixth, to check the dimensionality of a zero-correlation model using PCA.

Following these six steps should lead to a more parsimonious model, allowing healthy and converging reduced models while considering the concerns by Barr et al (2013) of increasing type I errors and retaining as much statistical power as possible (Matuschek et al., 2017).

## 3.5 Misspecifications in the error distribution

The multilevel model will be estimated using the ML estimator. ML is a method of finding the mean and variance values for the observations that maximizes the probability, or likelihood, of observing the data from the model (Kuttatharmmakul et al., 2000). Other than this brief description, the contents of this section is the assumptions for residuals to achieve correct standard errors and inference for MLM in ML and restricted maximum likelihood

(REML). If the assumptions are not met or been shown in literature to still be tolerated, then a robust estimator should be used to decrease standard error bias.

REML is a modified approach to ML estimation that uses information on loss of degrees of freedom for estimating variance components when population effects are included in the model. Other assumptions are considered equal between the two methods. Leading to unbiased variance and covariances estimates and higher precision than ML (Liu et al., 2017; Baayen et al., 2008).

ML is asymptotic and assumes large sample sizes for all levels in MLM. This assumption means that maximum likelihood also assumes normal distributions in accordance with the central limit theorem for all variance elements in the model. According to Nalborczyk et. al (2019) estimating MLM with maximum-likelihood methods can be problematic because the data may not contain enough information to estimate the high number of parameters present in the random effects structure.

For population effects, if conditional residuals are not normal or heteroscedastic, then inference based on asymptotic standard errors can be considered robust if the heteroscedastic variance does not depend on a covariate with interaction with time. Population effects are also robust when the covariance structure is misspecified. (Jacqmin-Gadda et al., 2007).

For estimates in the random structure with less than 100 groups the confidence intervals may be biased. With between 24 and 30 groups an operating alpha level of about 6.4% with a nominal significance level of 5% can be expected according to Maas and Hox (2004a). Standard errors of group estimates were 15% smaller with 30 groups than with an adequate sample size Maas and Hox (2004b).

Some of these weaknesses can be overcome by using robust standard errors estimations like the CR2 correction or robust estimation methods like the bias-reduced linearization estimator or the robust scoring equations estimator (Huang et. al. 2022; Koller, 2016)

# 4 Method and data

This chapter will examine the data structure and material, the maximal formulation of the model in accordance with Barr et al. (2013) and the model reduction procedure to achieve a converging and parsimonious model by Bates et al. (2015).

The subject of the research is all patients treated within the publicly funded somatic specialist healthcare providers in Norway aggregated at the DRG level. The research design is exploratory, attempting to ascertain the presence of an association and relationship between admissions and the profit of treating a patient within a DRG. The model can separate the effects of profit on individual DRGs, DRGs within specific hospitals and the whole population of treatments. It can also increases the power of the analysis by decreasing the number of observations needed to answer the research question as described by the design effect.

## 4.1 Data Structure

A nested structure occurs when each nested factor only occurs for one of the nesters. In other words, the observations for DRG *i* in each hospital *j* are specific to the hospital *j* and are different to other hospitals. A crossed structure occurs when the observations in a factor occur equally for all nesters. Again, in other words, that each DRG observation is similar for all hospitals *j* (Grace-Martin, 2020).

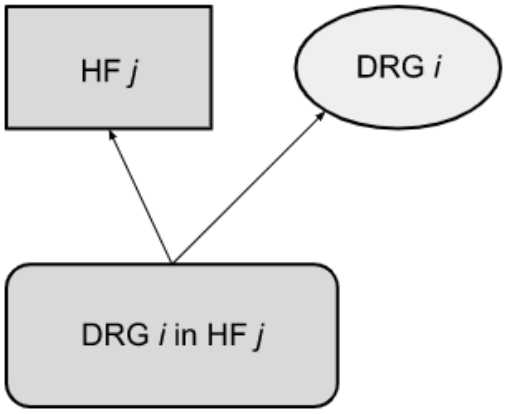


*Figure 2 The impact of HF and DRG on DRGs within HFs for one data point*

As illustrated above, the DRGs are nested in hospitals, but the DRG-weights are not. The nested structure of the data impact the predictive variables more directly than in previous research on price like in Januleviciute et al. (2016) and Melberg et al. (2016). This is because of the cost variable used to calculate the profit is specific to the hospital where the expenses were accrued and occurs only in that hospital. This means that the different DRGs *i* are tied to specific hospitals *j*, giving each DRG the possibility of different institutional, administrative, and demographic contexts.

The price-weight of DRG *i*, however, is not tied to the hospitals and occurs equally in all hospitals that include DRG *i*, it is therefore crossed and not nested. Resulting in a nested crossed design common for complicated subject-item experiments. Where DRG *i* is nested in hospital *j* and each DRG *i* in hospital *j* is affected by the DRG-weight of DRG *i* which is not dependent on hospital *j*.

To clarifying the influence of and need of the different group levels according to Huang (2018). Take the example of the intercept of a DRG *i* in a hospital *j*. It may not be represented correctly by the mean of the intercepts for all DRG *i* and the mean the intercepts for all hospital *j*. Leaving a small deviation to be estimated by the DRG in hospital group. In other words, the portion of the variance that cannot account for by the mean intercept for DRGs *i* and hospitals *j separately* are estimated in the DRG within hospital group.

The relationship can be expressed more directly in the figure below that includes 3 HFs and 3 DRGs.

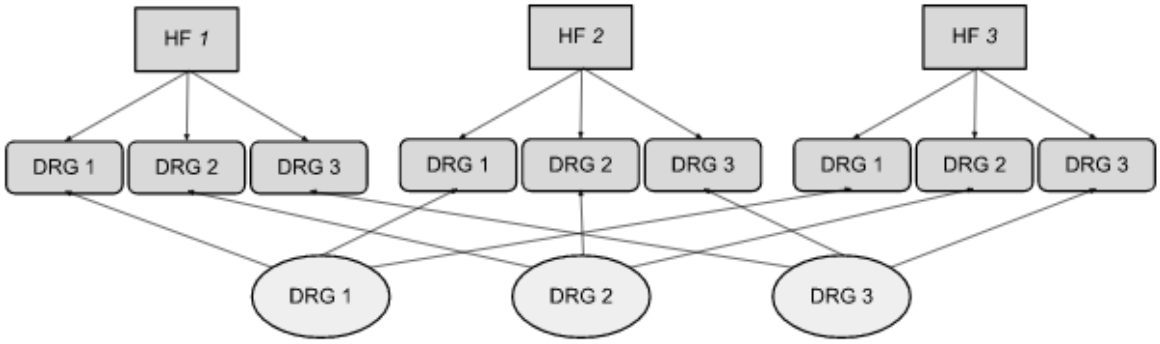


*Figure 3 Illustration of data dependency in crossed and nested design*

## 4.2 Data material

The data is secondary data received from two sources each at the HF and RHF level that, respectively, supplied cost data and DRG-weights data. The RHF also supplied the aggregated demographic variables for age and gender and the length of stay for each DRG within hospitals from the Norwegian patient registry (NPR). Because the data was received from two different sources, there was an average of 2.4% discrepancy in the total number of admissions for each DRG in each hospital. The cost data was adjusted to fit the admissions connected with the DRG-weight data.

The collected data included 49123 observations of 901 DRGs in 25 hospitals. 10603 observations of 223 DRGs were removed after balancing the panel. This was done to remove changes and substitutions that might happen in the DRG-system. Other removed observations were specialized DRGs where two or less hospitals administered the treatment, DRGs with a weight of 0 and rehabilitation DRGs 462A and 462B that have a scaling DRG-weight. After these removals the remaining data for analysis consisted of 8839 yearly observations for 611 DRG in 18 hospitals from 2018 to 2021.

The random variables that are available for use in the model for each DRG are admissions, the difference between DRG weight and cost in DRG-points (DRGP), DRG-weight (DRGW), change in DRG-weight (dDRGW), age, gender, and length of stay (LOS). Admissions are transformed with the natural logarithm based on the Box-Cox test, improving the normality of the data. The profit, price and change in price are measured as DRG-points, where 1 DRG-point is equal to the NATC $M_t$ for year *t*. Age is in years, gender is the percentage of female patients and LOS is number of days in treatment.

Table 1: Descriptive statistics

| Variable | Mean | Median | SD | Min | Max |
|---|---|---|---|---|---|
| ln(Adm) | 4.77 | 4.44 | 1.81 | 1.61 | 10.85 |
| DRGP | -0.13 | -0.02 | 0.85 | -34.55 | 15.36 |
| DRGW | 1.09 | 0.66 | 1.97 | 0.00 | 29.87 |
| dDRGW | 0.01 | 0.00 | 0.21 | -5.57 | 4.43 |
| Age | 52.39 | 55.96 | 18.05 | 0.00 | 91.33 |
| Gender | 0.54 | 0.50 | 0.24 | 0.00 | 1.00 |
| LOS | 144.05 | 25.99 | 427.93 | 0.00 | 15754.00 |

Descriptive statistics for all years can be seen in table 1. Some aspects of the data are worthy of elaboration. Firstly, the differences between the mean and median of the variables indicate that some of the distributions are skewed. Secondly, the funding-related variables DRGP, DRGW and dDRGW all have extreme minimum and maximum values. For all 3, the extreme values come from single year spikes or a few highly weighted DRGs, mainly tracheostomies in DRG 482 and 483 and neonatal care for children with low birthweights in DRGs 385C, 386N, 388A and 389A. DRGW shows a minimal value of 0 as DRG 809R has a DRG-weight of below 0.005 in one of the four years.

Thirdly, the minimum and maximum values of the patient characteristic variables also have some extreme values. The minimum value of 0 for age indicate birth related DRGs, for gender it indicates exclusively male diagnoses and for LOS it indicates outpatient treatment DRGs. The maximum values for gender are exclusively female DRGs.

Table 2 shows the mean values and standard deviations of admissions, DRGP, DRGW and number of DRGs that were treated in each hospital continuously between 2018 and 2021.

Table 2: Mean values for Hospitals

| HF | Admissions | SD | DRGP | SD | DRGW | SD | Number of DRGs |
|---|---|---|---|---|---|---|---|
| 1 | 879.87 | 2144.75 | -0.03 | 1.03 | 1.23 | 2.26 | 521 |
| 10 | 412.19 | 918.99 | -0.23 | 0.74 | 0.95 | 1.78 | 456 |
| 11 | 1662.45 | 4570.21 | -0.68 | 1.36 | 1.35 | 2.38 | 599 |
| 12 | 685.29 | 1669.70 | -0.03 | 0.58 | 1.07 | 1.85 | 526 |
| 13 | 833.93 | 2100.72 | -0.26 | 1.01 | 1.31 | 2.33 | 581 |
| 14 | 730.49 | 1841.67 | 0.08 | 0.52 | 1.07 | 1.85 | 527 |
| 15 | 655.99 | 1683.93 | -0.02 | 1.39 | 1.16 | 2.22 | 515 |
| 16 | 608.71 | 1495.49 | 0.04 | 0.78 | 1.09 | 1.95 | 470 |
| 17 | 508.27 | 1291.31 | -0.38 | 1.02 | 1.28 | 2.30 | 548 |
| 18 | 937.93 | 2402.39 | 0.03 | 0.64 | 1.15 | 1.92 | 532 |
| 2 | 248.98 | 547.39 | -0.11 | 0.81 | 0.62 | 0.78 | 313 |
| 3 | 286.24 | 633.80 | -0.06 | 0.50 | 0.68 | 0.89 | 348 |
| 4 | 1065.91 | 2760.48 | -0.12 | 0.62 | 1.33 | 2.35 | 587 |
| 5 | 355.83 | 853.75 | -0.17 | 0.45 | 0.78 | 0.95 | 391 |
| 6 | 385.67 | 908.32 | -0.07 | 0.49 | 0.92 | 1.61 | 441 |
| 7 | 729.31 | 1881.37 | -0.07 | 0.58 | 1.03 | 1.83 | 504 |
| 8 | 369.79 | 939.22 | -0.08 | 0.66 | 0.90 | 1.64 | 431 |
| 9 | 723.01 | 1817.49 | -0.09 | 0.57 | 1.17 | 2.16 | 549 |

The groups in the data are unbalanced. The number of DRGs present does not directly imply that a hospital with 587 DRGs in the sample treated all DRGs of a hospital with only 313 DRG in the sample. However, because the treatment of most specialized DRGs is concentrated at the largest hospitals, it is reasonable that the hospital with 587 DRGs includes a large part of DRGs treated in the hospital with 313 DRGs.

Table 3: Correlation matrix

| | lnAdm | DRGP | DRGW | dDRGW |
|---|---|---|---|---|
| lnAdm | 1.0000000 | 0.0701563 | -0.2932440 | -0.0303297 |
| DRGP | 0.0701563 | 1.0000000 | -0.1957459 | 0.0752397 |
| DRGW | -0.2932440 | -0.1957459 | 1.0000000 | 0.0084573 |
| dDRGW | -0.0303297 | 0.0752397 | 0.0084573 | 1.0000000 |

Table 2 shows the correlation matrix of the dependent and independent variables. Admissions is negatively correlated with DRGW at -29.3%, with dDRGW at -3% and positively correlated with DRGP at 7%. DRGPs correlation to DRGW and dDRGW is respectively -19.6% and 7.5%. The dependent variables all have a variance inflation factor very close to 1, indicating that they are not multicollinear.

The dependent variable ln(Adm), was transformed by the natural logarithm after the Box-Cox test was performed, improving the normality of the data. The transformation improved both the skewness and kurtosis of the data with skewness of 0,46 and kurtosis of 0,49 in the log form.

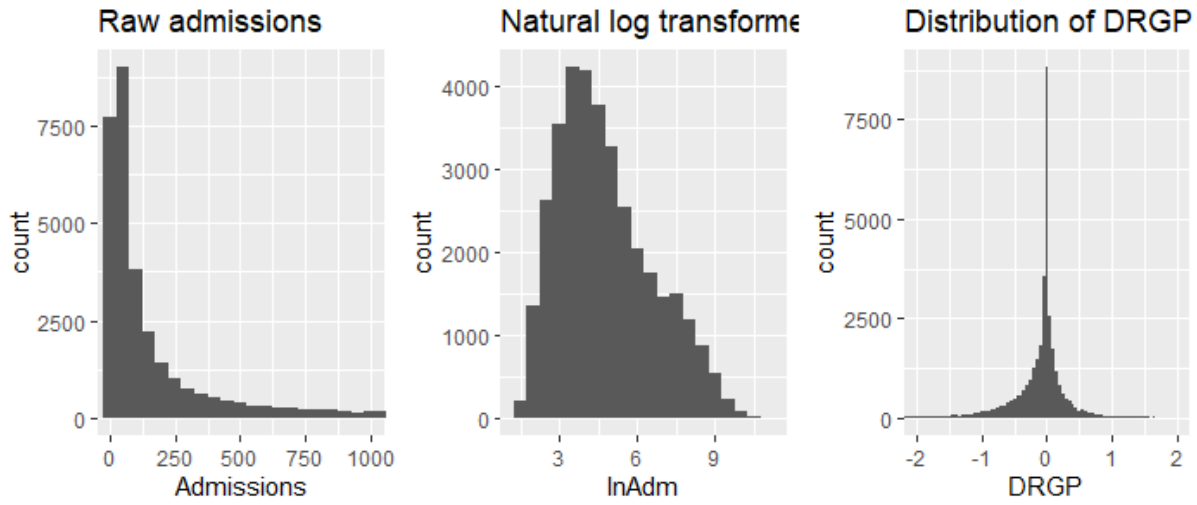


*Figure 4 Distribution of raw and log admissions, and DRG profit.*

Table 4: Distribution of ln(Adm)

| Min | 5% | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 95% | Max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1.6 | 2.3 | 2.6 | 3.1 | 3.6 | 4 | 4.4 | 4.9 | 5.5 | 6.4 | 7.5 | 8.2 | 10.9 |

Table 4 shows the transformed value of admissions at percentage intervals of the distribution with minimum and maximum values.

The main independent variable of interest, DRGP, is the result of expressing the costs for each patient in DRG-point form and subtracting it from the revenue for treating patients within each DRG with the following calculation.

$$\pi_{it} = g_{it} - \frac{C_{it}}{M_t y_t} \tag{11}$$

Where $DRGP_{it}$ is the profit of treatment and only the DRG-weight $g_{it}$ is used to express $p_{it}$ as the revenue for DRG *i* in year *t*. The costs $C_{it}$ were obtained as yearly monetary costs and reduced to DRG-point form to match the form of revenue by $M_t y_t$. This violates the relationship expressed in equation 1 but follows the assumptions of ABF-share = 100% from section 4.1.

Table 5: Distribution of DRGP

| Min | 5% | 10% | 20% | 30% | 40% | 50% | 60% | 70% | 80% | 90% | 95% | Max |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| -34.5 | -1 | -0.6 | -0.3 | -0.1 | -0.1 | 0 | 0 | 0 | 0.1 | 0.3 | 0.5 | 15.4 |

Table 5 shows the value of DRGP at percentage intervals of the distribution with minimum and maximum values. The distribution of DRGP can be seen in figure 4 and has a skewness of -9.31 and kurtosis of 265.

## 4.3 Model

This section will present the maximal model without patient characteristic data. The patient characteristic data was eliminated from inclusion in early testing due to overparameterization in relation to the data that was available.

The model has 3 levels for coefficient $b_{1ij}$ and intercept $b_{0ij}$ and two levels for coefficients $b_{2i}$ and $b_{3i}$. In the context of the hyperparameters of the coefficients for independent variables DRGP $\pi_{ijt}$, DRGW $p_{it}$ and dDRGW $\Delta p_{it}$, the grand mean is the population effect. Each have their own hyperparameters where the group variance terms *v* represents the deviation of DRG *i* from hospital (HF) *j* mean, *w* the deviation of HF *j* mean from the grand mean and *u* is the deviation from grand means of DRG *i*.

The level 1 equation for the maximal model is as follows.

$$ln(\pi_{ijt}) = b_{0i} + b_{0ij} + T_t + b_{1ij}\pi_{ijt} + b_{2i}p_{it} + b_{3i}\Delta p_{it} + \varepsilon_{ijt} \quad (12)$$

Where $y_{ijt}$ is the number of patients treated, and $\pi_{ijt}$ is the profit per patient for DRG $i$ in HF $j$ for year $t$. $b_{0ij}$ is the intercept for DRG *i*, in HF *j* and $b_{0t}$ the time effect. $p_{it}$ is the price and $\Delta p_{it}$ is the change in price from the previous year for DRG *i* in year *t*.

The level 2 equations for the coefficients of DRGs within HFs are

$$b_{0ij} = \gamma_{00j} + v_{0ij} \quad (13)$$

$$b_{1ij} = \gamma_{10j} + v_{1ij} \quad (14)$$

Where the coefficients in equation 1 of the intercept $b_{0ij}$ and slope $b_{1ij}$ of $\pi_{ijt}$, respectively are calculated by the hyper parameters the HF *j* mean intercept $\gamma_{00j}$ and slope $\gamma_{10j}$ and the deviations $v_{0ij}$ and $v_{1ij}$ of DRG *i* within HF *j*.

The level-3 equations are similarly calculating the mean intercept and slope of HF *j* from the grand mean.

$$\gamma_{00j} = \delta_{000} + w_{00j} \quad (15)$$

$$\gamma_{10j} = \delta_{100} + w_{10j} \quad (16)$$

Where the HF *j* hyperparameters for intercept $\gamma_{00j}$ and slope $\gamma_{10j}$ are calculated from the of the grand mean intercept $\delta_{000}$ and slope $\delta_{100}$ and $w_{00j}$ and $w_{10j}$ is the deviation of.

The level 2 equations for the coefficients in the DRG group are

$$b_{0i} = \delta_{000} + u_{0i} \quad (17)$$

$$b_{2i} = \gamma_{20} + u_{2i} \quad (18)$$

$$b_{3i} = \gamma_{30} + u_{3i} \quad (19)$$

The DRG coefficients for the intercept $b_{0i}$, and slopes $b_{2i}$ and $b_{3i}$ are the result of the grand intercept $\delta_{000}$, and population effects $\gamma_{20}$ and $\gamma_{30}$ and the deviation for DRG *i* for the intercept $u_{0i}$, and slopes $u_{2i}$ and $u_{3i}$.

The variance-covariance matrix for group level error terms estimated in his model are for HF in equation 20, DRGs in HF in equation 21 and DRG in equation 22.

$$\begin{pmatrix} v_{0ij} \\ v_{1ij} \end{pmatrix} \sim N \begin{pmatrix} 0 & \tau_{00}^2 & \tau_{01} \\ 0' & \tau_{01} & \tau_{10}^2 \end{pmatrix} \tag{20}$$

$$\begin{pmatrix} w_{00j} \\ w_{10j} \end{pmatrix} \sim N \begin{pmatrix} 0 & \psi_{00}^2 & \psi_{01} \\ 0' & \psi_{01} & \psi_{10}^2 \end{pmatrix} \tag{21}$$

Where the …

$$\begin{pmatrix} u_{0i} \\ u_{2i} \\ u_{3i} \end{pmatrix} \sim N \begin{pmatrix} 0 & \varphi_{00}^2 & \varphi_{01} & \varphi_{02} \\ 0, & \varphi_{01} & \varphi_{10}^2 & \varphi_{12} \\ 0 & \varphi_{02} & \varphi_{12} & \varphi_{20}^2 \end{pmatrix} \tag{22}$$

Substituting equations 13 to 19 in equation 12 gives the formulation in equation 23

$$\begin{aligned} ln(y_{ijt}) = (\delta_{000} + u_{0i} + w_{00j} + v_{0ij}) + T_t + (\delta_{100} + w_{00j} + v_{1ij})\pi_{ijt} \\ + (\gamma_{20} + u_{2i})p_{it} + (\gamma_{30} + u_{3i})\Delta p_{it} + \varepsilon_{ijt} \end{aligned} \tag{23}$$

The model can then be rephrased again by changing the directionality of the levels to illustrate the form of the fixed effect and random effect structure more clearly, visualized by the random structure is brackets this formulation is more like the output from the software that will be presented in section 5.

$$\begin{aligned} ln(y_{ijt}) = b_0 + T_t + b_1\pi_{ijt} + b_2 p_{it} + b_3 \Delta p_{it} \\ + [u_{0i} + v_{0ij} + w_{00j} + (v_{1ij} + w_{10j})\pi_{ijt} + u_{2i}p_{it} + u_{3i}\Delta p_{it} + \varepsilon_{ijt}] \end{aligned} \tag{24}$$

Where the first unbracketed elements are population effects, intercept $b_0$, time effect $T_t$, profit effect $b_1$, price effect $b_2$ and change in price effect $b_3$. $u_{0i}$, $v_{0ij}$ and $w_{00j}$ is the deviation from the grand mean for DRG *i*, HF *j* and DRG *i* in HF *j*. The other parameters in the random structure are the deviations of profit for hospital *j* $w_{10j}$from $b_1$, $v_{1ij}$ is the deviation of DRG *i* from the mean of HF *j* and $w_{10j}$ is the deviation of HF *j* from $b_1$. $u_{2i}$ and $u_{3i}$ is the deviation of price and change in price in DRG *i* from $b_2$ and $b_3$, respectively. The final element $\varepsilon_{ijt}$ is the individual time *t* deviation for DRG *i* in HF *j*.

It is easy to see the function of multilevel models in the final formulation in equation 24. Dividing the residual variance into groups allows for more variance to be modeled from the population effects by the different error terms in the different groups.

## 4.4 Testing procedure

The testing procedure involves model comparison with the procedure from Bates et al. (2015) and residual analysis on the final model to evaluate conditions for inference from population effects. The maximal model described in section 4.2 did not converge, therefore, a reduction in model complexity was necessary. In the first step, the maximal model met the criterion for number of supported variance dimensions, so the second step of reducing variance components was not needed. For the third step, several models with reduced covariances converged, but all had significant loss of goodness-of-fit from the maximal model. In the fourth step, 3 specifications converged, however all had significant loss of goodness-of-fit according to RLT and lower log likelihood than the maximal model without correlations. Step five did not improve the converging models with a variable removed to a significant degree. Step six was not relevant to this model because the maximal model was computable.

The correlation reduced models can be viewed in table 6 below. The maximal model is described with code from the *lmer* function in the *lme4* package in R. Descriptions for subsequent models include the changed code snippets from the maximal model. The LRT was calculated using the *lrtest* package and AIC and BIC were calculated with ML instead of REML models using the *flexplot* package in R. Reduced model number 2 and 4 with no correlation for respectively HF:DRG and DRG were excluded from consideration because they did not converge.

The model reduction suggestions in steps 4 and 5 were executed together. All attempts to remove variance components resulted in significantly worse fitting models. The *a priori* assumption of the author was that changes in price (dDRGW) was the least informative variable. However, the removal of changes in price from both the maximal model and the best-fitting no-correlation model was significant.

Table 6: Model selection summary

| Models | Description | LRT | p.value | AIC | BIC |
|---|---|---|---|---|---|
| Maximal | The full model as specified in 4.2<br>lmer(lnAdm ~ 1 + Year +<br>DRGP + DRGW + dDRGW +<br>(1 + DRGW + dDRGW \| DRG) +<br>(1 + DRGP \| HF) +<br>(1 + DRGP \| HF:DRG)) | -15081 | | | |
| No HF | (1 + DRGP \|\| HF) | -15084 | 0.02268 * | 30205.10 | 30366.09 |
| No HF:DRG | (1 + DRGP \|\| HF:DRG) | - | - | - | - |
| No HF or HF:DRG | (1 + DRGP \|\| HF) +<br>(1 + DRGP \|\| HF:DRG)) | -15084 | 0.03875 * | 30204.41 | 30356.92 |
| No DRG | (1 + DRGW + dDRGW \|\| DRG) | - | - | - | - |
| No HF and DRG | (1 + DRGW + dDRGW \|\| DRG) +<br>(1 + DRGP \|\| HF:DRG) | -15133 | < 2.2e-16 *** | 30298.21 | 30433.78 |
| No DRG and HF:DRG | (1 + DRGW + dDRGW \|\| DRG) +<br>(1 + DRGP \|\| HF) | -15131 | < 2.2e-16 *** | 30293.83 | 30429.40 |
| No correlations | (1 + DRGW + dDRGW \|\| DRG) +<br>(1 + DRGP \|\| HF) +<br>(1 + DRGP \|\| HF:DRG) | -15134 | < 2.2e-16 *** | 30297.21 | 30424.31 |

The attempts to fit a reduced model without loss of goodness-of-fit were unsuccessful for all 5 steps. The procedure found a converging, non-singular models in step 3 and no significant improvements over reduced correlation models in sequential steps. The candidates that were evaluated for final model fit were the 2 reduced models with reduced covariance structure for HF, and HF and DRGs in HFs (HF:DRG). When tested against each other using LRT, there was no difference between the models or when individually tested against the maximal model. Suggesting that the correlation between the intercept and DRGP coefficient in the HF:DRG group were not significantly different from 0. Correlations for the selected reduced model were removed from both groups because of the non-significant correlation in the HF:DRG group. This seems to be aligned with the reasoning by Bates et al. (2015) for model simplification when estimating population effects.

The variance-covariance matrix for the main model becomes simplified for two out of the three groups. Removing covariances between the intercept and slope of DRGW for HF *j* and DRG *i* in HF *j*.

$$\begin{pmatrix} v_{0ij} \\ v_{1ij} \end{pmatrix} \sim N \begin{pmatrix} 0 & \tau_{00}^2 & 0 \\ 0' & 0 & \tau_{10}^2 \end{pmatrix}, \begin{pmatrix} w_{00j} \\ w_{10j} \end{pmatrix} \sim N \begin{pmatrix} 0 & \psi_{00}^2 & 0 \\ 0' & 0 & \psi_{10}^2 \end{pmatrix} \quad (25)$$

$$\begin{pmatrix} u_{0i} \\ u_{2i} \\ u_{3i} \end{pmatrix} \sim N \begin{pmatrix} 0 & \varphi_{00}^2 & \varphi_{01} & \varphi_{02} \\ 0, & \varphi_{01} & \varphi_{10}^2 & \varphi_{12} \\ 0 & \varphi_{02} & \varphi_{12} & \varphi_{20}^2 \end{pmatrix} \tag{26}$$

Assumptions of linearity, normality, and homogeneity of variance will be tested on the selected model. The residual assumptions were tested by visual inspection. Visually inspecting residuals is contested by some, but remains a highly used approach (Yang, 2012). For testing conditional residuals this method closely resembles visual tests for non-multilevel models.

# 5 Results

This chapter presents the results from the analysis. From the theory in chapter 2, the expected results of the population effects based on previous research was firstly, that there would be a negative relationship between the price and the number of admissions and secondly a positive relationship between changes in price and number of admissions. The time effect was assumed to be equal between 2018 and 2019, negative for the year of the pandemic restrictions in 2020 and a rebound effect in 2021. The effect of profit on number of treatments does not have previous studies to compare to directly for the population effect, as the Liang (2015) study only included a small portion of surgical DRGs. The population effect of profit was, based on the theoretical framework of financial incentives in general, expected to be small in a positive direction or not significantly different from 0.

The expectation of finding a negative price effect is because highly weighted DRGs occupy a larger share of the maximally allowed activity from fixed funding. The profitability of these DRGs would have to be higher proportional to the difference in weight. When considering the mechanisms in the ABF system to adjust profit towards 0, it is unlikely that highly weighted DRGs have a profit margin proportional to their budget share when compared to lower weighted DRGs.

## 5.1 Population effects

The result from the selected model specification is presented in table 7 with estimates for population effects and random effect variances. The first section of the table shows the population effects. All effects were significant when using the maximum likelihood standard

error. The grand mean (Intercept) is high at 4.5459 and which is above the median of the response variable. The differences between years are 0.0352, -0.02 and 0.0416 respectively for 2019, 2020 and 2021 when compared to the intercept of 2018.

The coefficient for profit (DRGP) was 0.0321, the coefficient for price (DRGW) was -0.2877 and the coefficient for change in price (dDRGW) was -0.01888.

Table 7: Model Summary

| | Term | Estimate | St. error | Statistic | p-value |
|---|---|---|---|---|---|
| **Population effects** | | | | | |
| | (Intercept) | 4.5459 | 0.161 | 28.1764 | 0 |
| | Year2019 | 0.0352 | 0.005 | 7.3041 | 2.85e-13 |
| | Year2020 | -0.02 | 0.005 | -4.1492 | 3.3e-05 |
| | Year2021 | 0.0416 | 0.005 | 8.4718 | 2.508e-17 |
| | DRGP | 0.0321 | 0.007 | 4.718 | 2.4e-06 |
| | DRGW | -0.2877 | 0.027 | -10.5802 | 0 |
| | dDRGW | -0.1888 | 0.065 | -2.9141 | 0.0036 |
| | | Variance | St. dev | | |
| **Random effects** | | | | | |
| HF | (Intercept) | 0.3609 | 0.601 | | |
| | DRGP | 5e-04 | 0.022 | | |
| HF:DRG | (Intercept) | 0.2356 | 0.485 | | |
| | DRGP | 0.005 | 0.069 | | |
| DRG | (Intercept) | 3.3046 | 1.818 | | |
| | DRGW | 0.1653 | 0.407 | | |
| | dDRGW | 1.3236 | 1.15 | | |
| Error | Observations | 0.6575 | -0.811 | | |

## 5.2 Random effects

The random effects are indexed by grouping. Most of the variance of admissions can, according to the ICC, be explained by the DRGs at 82.1% of total variance. The variance of DRGs in HFs is and only accounts for 6.4% of the total variance. This is also the case for HFs, that can explain 9.7%. The grouping of the variance resulted in a design effect of 3.94.

The intercepts specific to HFs had a variance of 0.309, specific to DRG had a variance of 3.3046 and specific to DRGs in HFs had a variance of 0.2356. The effect of DRGP for HFs had a variance of 0.0005 and for DRGs in HFs a variance of 0.3609. The effect of DRGW had a variance of 0.1653 and the effect of dDRGW had a variance of 1.13236.

The correlations modeled for coefficients that varied by DRG were -0.811 between the intercept and DRGW, -0.257 between the intercept and dDRGW and -0.257 between DRGW and dDRGW.

Other parameters can be extracted from the random structure, however the forced 0 correlation between the intercept and DRGP for HFs and DRGs within HFs limits the usefulness of the results. A more detailed summary of the random effects can be seen in table 8.

Table 8 : Descriptive statistics of random structure results

| Variable | Mean | SD | Min | Max |
|---|---|---|---|---|
| **HF group** | | | | |
| Intercept | 0.000 | 0.601 | -1.219 | -1.219 |
| Intercept SD | 0.067 | 0.001 | 0.066 | 0.069 |
| DRGP | 0.000 | 0.017 | -0.025 | 0.033 |
| DRGP SD | 0.014 | 0.002 | 0.010 | 0.016 |
| **HF:DRG group** | | | | |
| Intercept | 0.000 | 0.453 | -3.494 | 2.367 |
| Intercept SD | 0.173 | 0.020 | 0.163 | 0.449 |
| DRGP | 0.000 | 0.012 | -0.145 | 0.234 |
| DRGP SD | 0.068 | 0.004 | 0.017 | 0.069 |
| **DRG group** | | | | |
| Intercept | 0.000 | 1.766 | -4.083 | 4.892 |
| Intercept SD | 0.341 | 0.270 | 0.130 | 1.780 |
| DRGW | 0.000 | 0.325 | -0.887 | 0.800 |
| DRGW SD | 0.240 | 0.045 | 0.018 | 0.350 |
| dDRGW | 0.000 | 0.847 | -6.724 | 3.465 |
| dDRGW SD | 0.688 | 0.363 | 0.016 | 1.141 |

The mean effects for HFs can be viewed in table 9 in Tables and Figures. Where the intercept represents the conditional mean of the HFs and indicates the differences in mean admissions in HFs from the grand mean. The same can be said for DRGP, where the conditional mean is the difference in effect of DRGP at HF *j* from the population effect. The HF deviations for the intercept vary from -1.219 to 1.042 and for DRGP from -0.025 to 0.033.

The coefficients for DRG group variables can be viewed in table 10 in Tables and Figures. A full list of coefficients for DRGs within HFs group are extremely long and will not be reported.

## 5.3 Profit elasticity of admissions

Figure 5 shows elasticity of DRG admissions to profit as a linear function of profit according to the definition in equation (2) aggregated at the population level. The absolute value of the elasticity increases with the absolute value of DRGP. The thick blue line is the elasticity of the population and black lines are DRG elasticities aggregated to the HF level. The red line is the population mean DRGP, and red dots are HF specific elasticity at HF specific mean DRGP.

The figure shows that there may be different elasticities between hospitals. The HF elasticities calculated from analysis coefficients has a spread of 5.8% when DRGP is at either -1 or 1 Each respectively has a minimum and maximum elasticity of -0.7% and -6.5%, and 0.7% and 6.5%. Indicating that the DRG admissions at different HFs have varying responsiveness to changes in profitability.

The elasticity changes in relation to the positive or negative value of DRGP, meaning that the admissions of highly profitable or unprofitable DRGs are relatively more elastic to changes in DRGP. The admissions of DRGs are inelastic to changes in DRGP while DRGs with DRGP of 0 are perfectly inelastic.

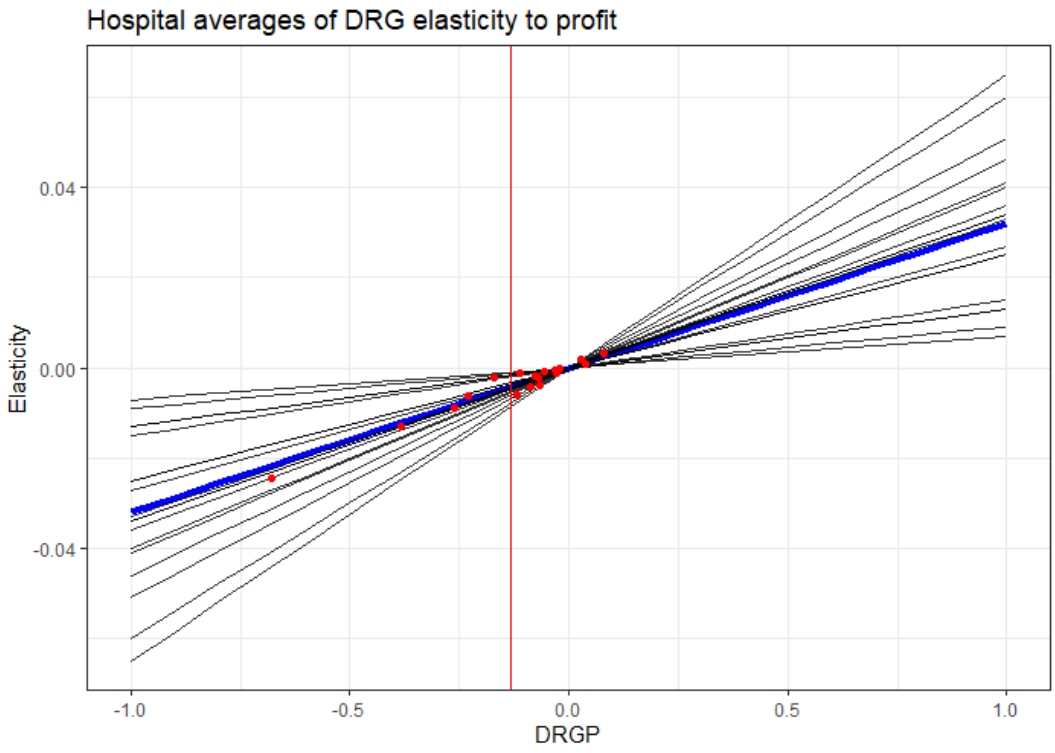


*Figure 5 Profit elasticity of DRG admissions at hospital level*

## 5.4 Residual analysis

Figure 6 is used to evaluate linearity by plotting residuals against the response variable. The assumption of linearity holds if there are no systematic patterns in the plot. Nonrandom residual patterns could indicate the existence of nonlinear relationships between the response and predictive variables (Yang, 2012). The plot shows that the majority of residuals are close to 0, with no visible patterns.

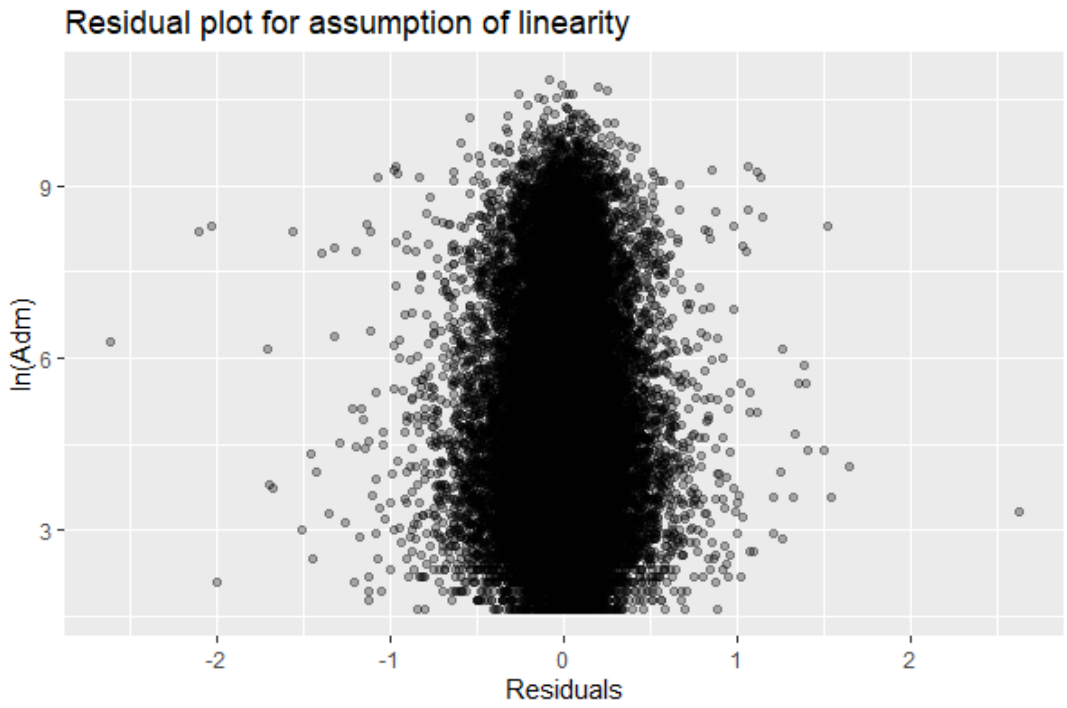


*Figure 6 Residual plotted against ln(Adm)*

Figure 7 is used to evaluate normality of residuals using methods in Yang (2012). In the left plot of figure 7 is the sample residual quantile against theoretical normal distribution quantiles. This plot indicates where in the distribution sample residuals diverge from the theoretical distribution. A completely normal distribution would all follow the diagonal line. The flatness of the points and diagonal line indicates ties in the data or a large amount of values close to the mean value of the distribution as seen in the density plot. The residuals have a skew of -0.316 and kurtosis of 9.2, indicating that the residuals are not normally distributed and has a too high peak and too fat tails.

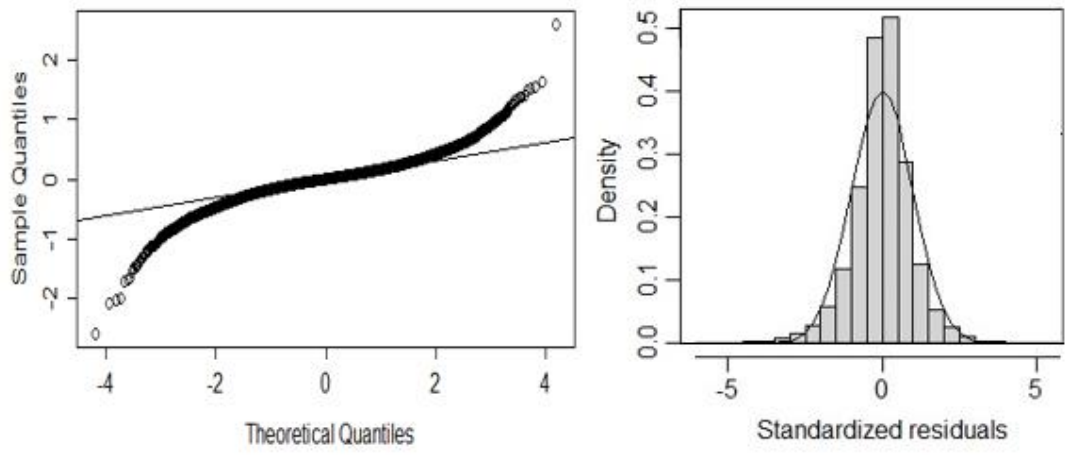


*Figure 7 Plot of residuals in sample against theoretical quantiles and distribution*

Heteroscedasticity is evaluated in figure 8, This figure shows residuals plotted against estimated values and clearly shows a non-homogenous variance of the residuals based on the fitted values for observations of the response variable. Residuals for larger fitted values have lower variance than low estimates.

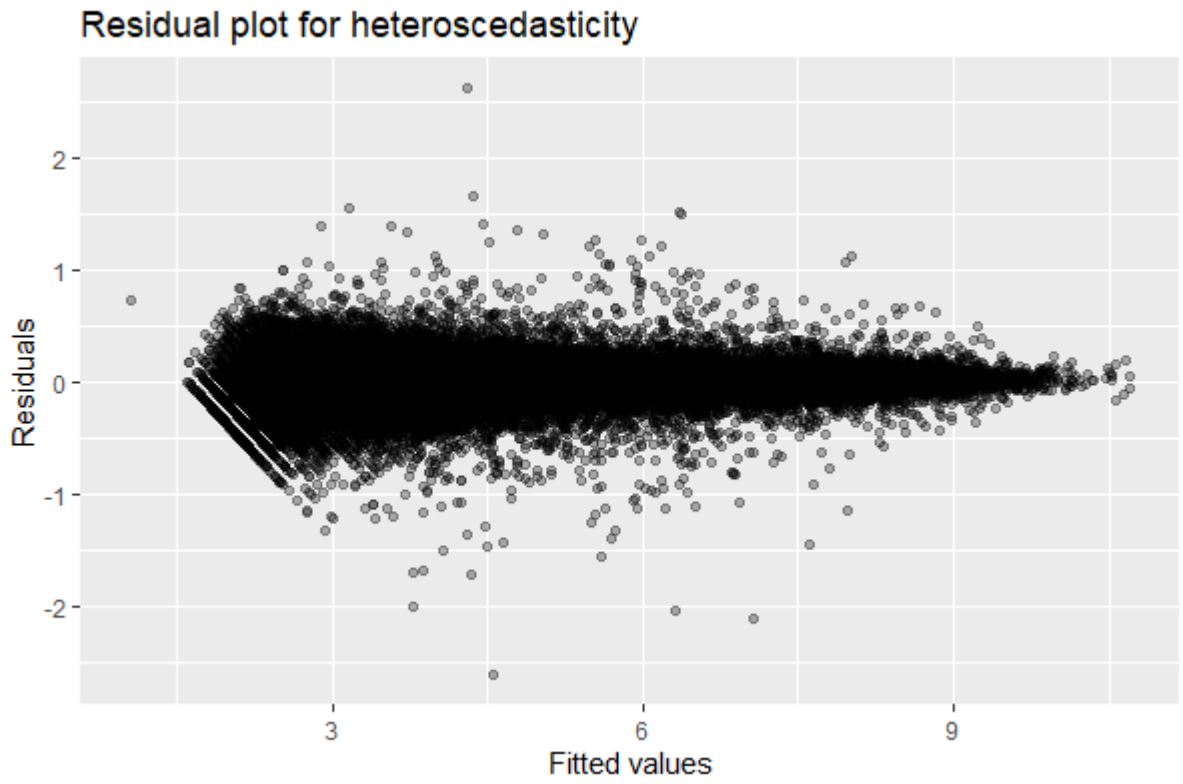


*Figure 8 Residuals plotted against fitted values*

# 6 Discussion

This thesis is focused on financial incentives. Investigating the effect of profit *ceteris paribus* at a national level using secondary, real-world data. Eliminating all other influence on treatment allocation within hospitals is not possible with the collected data, hospitals can be assumed to be required to be financially responsible and can therefore be influenced by financial incentives.

RQ 1 *asks if there is an association between the number of admissions and the profit incentive of DRGs*. The model estimates a linear function between the natural logarithm of admissions and DRG-points of profit for each DRG in the DRGP variable.

The results for DRGP showed significant effects at the population, HF and HF:DRG group levels, and has a small population effect on admissions of 0.0321.

The variables for price and changes in price are DRG specific and equal between all hospitals. From the DRG specific results, the own-price elasticity was -0.3136 at the mean value of price for all years. Januleviciute et. al. (2016) found a small own-price elasticity of 0.042. The difference between the two findings is very large and the unit of measurement is in different scales. Januleviciute et. al. (2016) used NOK and this thesis used DRG-points. Since there are both differences in model and unit of measurements, direct comparison between the results is not possible.

RQ 2 *asks to what the elasticity of admissions is in response to profit to inquire about the size of the effect of the profit incentive*. The positive directionality of the semi-elasticity of admissions to profit was consistent with the findings of Liang (2015) for the population effect. The profit elasticity as a function of the profit incentive seems plausible. Also, the elasticity reflects the adaptation predicted of Dranove (1987), as cited in Liang (2015), that hospitals will increase admissions of highly profitable DRGs. The result from the analysis adds the decreased admissions of negative profitability DRG and low responsiveness to small profit margins in either direction in a congruent way to the findings of Liang (2015) and prediction of Dranove (1987).

The study Januleviciute et al. (2016) questioned whether financial incentives “bite” within the Norwegian institutional context, partly because of the partial adoption of ABF and lack of recipients for profit outside hospital organizations. Solely for exogenous changes in price, this

uncertainty seems suitable. From the theory and results in this thesis, the assumption that the partial adoption impacts financial incentives to a large degree seems to be a misinterpretation of financial incentives in the Norwegian context. Based on Chalkley and Malcomson (1998) and the utility function by Biørn et al. (2003), public not-for-profit hospitals under prospective payment systems based on new public management principles still have innate organizational incentives to maintain healthy earnings to secure their existence. The effect of the fixed funding on decision-making in hospitals is as a limit to the total number of activity-based DRG-points produced, as expressed in equation (3).

A more appropriate question with regards to the fixed funding is whether the partial adoption increases the negative cross-price or profit elasticity of admissions of DRGs that are substitutes.

From the previous chapter, all population effects, except change in price, were significantly different from 0. This depends on the estimated confidence intervals. The ML estimator assumes a linear relationship between the dependent and independent variables and that the errors are normally distributed and homoscedastic (Maas & Hox, 2004b). Visual inspection of figure 6 did not show a non-linear formation in the residuals. The high kurtosis of the residuals in this model indicates a non-normal distribution with a larger proportion of observations around the mean, and in the tails, than the normal distribution as seen in figure 7. The residuals are also heteroscedastic, and their variance decreases with increasing values of admissions as seen in figure 8.

Despite these deviations from the assumed error specification, the population effect estimates and confidence intervals may still be valid. Jacqmin-Gadda et al. (2007) showed that parameter estimates were unbiased and standard errors were not increased with non-normal distributions. They also showed that population effects are robust to heterogenous residual variance when the variance is not dependent on covariates that have interactions with time. Examination of the residuals confirmed that the variance was dependent on the value of admissions, see the end of R-code in appendix 9.4, to which the model should be robust according to Jacqmin-Gadda et al. (2007).

Jacqmin-Gadda et al. (2007) does not test the two misspecifications together, but a premise for their testing of robustness to deviations in normality was the use of untransformed dependent variables. This resulted in density functions with much larger deviations from the

normal distribution than in the model of this thesis. The estimated effect of the profit incentive has a high p-values for the population effects. The influence of higher kurtosis on the standard errors should be limited. Therefore, the results from the analysis should be accepted as valid because of the robustness of the model to heteroscedasticity and relatively mild deviation from normality.

The use of both a robust estimator and robust standard error calculations was also attempted. However, the attempts were unsuccessful because of limited computational capacity and lack of function packages in *R* that could accommodate a crossed effect design.

Inference from the results of random structures are, in general, possible in MLM. The results may still be interesting for some to explore in this instance. However, the model has forced correlation between the grouped variables in the groups for HF and HF:DRG from the procedure by Bates et al. (2015) and both a misspecified error distribution and variance. The basis for the procedure by Bates et al. (2015) is also that the random structure is included in the model to increase the power of population effect estimates. The results from specific hospitals, DRGs or DRGs within hospitals from the random structure are unreliable.

An argument can be made, based on the results, that a multilevel model was unnecessary for early, exploratory research with few years of data. The random effect structure does increase the power of the test with respect to the population effects, but the number of observations and clusters necessary to support all estimate and variance components in the maximal model is very high compared to other methods.

The choice of simplified model based on the suggestions of Bates et. al (2015) could also have been incorrect due to the additional penalty to the reliability of profit effect results over change in price, which only affected the variance separated to the DRG group specifically. Removing an explanatory variable from DRG specific effects, to allow for correlations in groups that included the profit variable, could increase the usefulness of hospital specific results.

The major limitations of the analysis were the low number and quality of years included in the study which necessitated the removal of patient characteristic variables. These limitations impact both the reliability and validity of the results. If the collected patient characteristic variables had been included in the model, they would have occupied the same group variance space as DRGP and could impact the magnitude of the effect. Also, the two years that were

subject to the restrictions from measures to reduce the spread of the disease may have impacted the admission changes.

The data was also collected from two sources. The difference between the admissions of the two sources was adjusted to fit the RHF data. This could affect the price and profit variables for low admission DRGs. However, for the majority of DRGs the number of admissions should be high enough that average cost per patient was unlikely to be affected to a significant degree by costs from the missing observations that caused the 2.4% discrepancy between the data sources. The possibility that the scaling affected the financial variables is still present.

# 7 Conclusion

This thesis shows how analyzing profit in a divided funding healthcare system, and how adaptation of maximal multilevel models to limited data, is possible. The purpose of this study was to investigate systematic influence profit incentives in the Norwegian ABF system. The necessary cost data that allowed this analysis has not been available to previous studies. It was done using a multilevel model on the available data from the relatively short period from 2018 to 2021.

The profit incentive was operationalized as the DRG-point difference between revenue and cost for each DRG. A multilevel model was used to test if the data supported an association between the average profit margin and the number of admissions of DRGs. The results and residual analysis indicate that the association *is present* at the population level, but the differences between the effects for specific hospitals are unreliable.

Secondly, the elasticity was estimated to express the size of the effect on admissions relative to the profit incentive. The DRG admissions sensitivity to changes in profit has a linear relationship to the size of the profit incentive with a semi-elasticity of 3.21%. The size of the effect of profit could be overstated because of the missing degrees of freedom to include patient characteristics.

The major limitation of this study was the concessions made to the variance-covariance structure and independent variables to achieve a parsimonious model. More years of data seems to be necessary to accommodate a more complex structure and variables.

This thesis only examined a sliver of the legitimate or illegitimate strategies that could be utilized by hospitals to impact earnings. Allowing the financial incentive of profit to impact

decisions could be both legitimate and illegitimate, however the result from this thesis seems to align with the definition of cream skimming by Martinussen and Hagen (2009) and indicates that cream skimming is present in the Norwegian healthcare system.

More research covering either more years of data or a different model specification is needed to confirm the presence of cream skimming and the differences in effect of the profit incentive between hospitals. More research is also.

Future research should especially utilize the new cost data in other areas of "hospital misbehavior". Such as the *within* DRG patient selection or upcoding. Researchers could also attempt to identify DRGs that are substitutes and complementary with regards to profit.

Other angles that could also be investigated are the difference of effect between the categorizations of medical or surgical and elective or emergency as used in Januleviciute et al. (2016), or DRG-groups as used in Melberg et al. (2016).

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# 9 Appendix

## 9.1 Table 8: HF coefficients

Table 9: Results for HFs

| HF | Intercept | SD | DRGP | SD |
|---|---|---|---|---|
| 01 | 0.500 | 0.0664 | 0.009 | 0.0142 |
| 02 | -1.219 | 0.0689 | -0.023 | 0.0118 |
| 03 | -0.994 | 0.0683 | -0.017 | 0.0159 |
| 04 | 0.670 | 0.0660 | 0.019 | 0.0133 |
| 05 | -0.735 | 0.0677 | -0.015 | 0.0159 |
| 06 | -0.394 | 0.0671 | 0.028 | 0.0158 |
| 07 | 0.129 | 0.0666 | 0.001 | 0.0150 |
| 08 | -0.501 | 0.0672 | -0.007 | 0.0163 |
| 09 | 0.239 | 0.0662 | 0.014 | 0.0137 |
| 10 | -0.373 | 0.0670 | -0.005 | 0.0142 |
| 11 | 1.042 | 0.0662 | 0.004 | 0.0101 |
| 12 | 0.149 | 0.0664 | -0.019 | 0.0144 |
| 13 | 0.484 | 0.0661 | 0.002 | 0.0119 |
| 14 | 0.338 | 0.0664 | 0.008 | 0.0152 |
| 15 | 0.157 | 0.0665 | -0.025 | 0.0140 |
| 16 | -0.084 | 0.0668 | -0.007 | 0.0151 |
| 17 | 0.030 | 0.0663 | 0.002 | 0.0111 |
| 18 | 0.562 | 0.0663 | 0.033 | 0.0149 |

## 9.2 Table 9: DRG coefficients

Table 10: Coefficients for DRG

| DRG | Intercept | SD | DRGW | SD | dDRGW | SD |
|---|---|---|---|---|---|---|
| 100 | -0.026 | 0.1871 | 0.070 | 0.2512 | 0.143 | 1.0955 |
| 101 | -0.957 | 0.2755 | 0.295 | 0.2213 | 1.650 | 0.2920 |
| 102 | -0.996 | 0.2002 | 0.379 | 0.2333 | 1.780 | 0.2936 |
| 104A | -0.320 | 1.7798 | -0.059 | 0.3470 | -0.200 | 0.5253 |
| 104B | 0.577 | 1.0708 | 0.234 | 0.1472 | 0.156 | 0.9363 |
| 107A | -0.640 | 1.3883 | 0.071 | 0.2934 | 0.228 | 0.0636 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 107A | -0.640 | 1.3883 | 0.071 | 0.2934 | 0.228 | 0.0636 |
| 107C | -0.285 | 1.6877 | 0.352 | 0.2683 | 0.198 | 0.0775 |
| 108 | -1.495 | 1.5713 | 0.299 | 0.2408 | 0.372 | 0.2045 |
| 109N | -0.850 | 1.3411 | 0.258 | 0.1596 | 0.072 | 0.0906 |
| 110 | -0.783 | 0.6453 | 0.309 | 0.1040 | 0.207 | 0.4893 |
| 111 | -0.168 | 0.7117 | -0.140 | 0.2050 | 0.175 | 0.4708 |
| 112A | 1.333 | 0.5384 | -0.142 | 0.3022 | 1.426 | 0.2772 |
| 112B | 1.677 | 0.5442 | -0.015 | 0.2346 | 0.174 | 0.1021 |
| 112C | 0.867 | 0.3295 | -0.231 | 0.2636 | -1.261 | 0.3553 |
| 112D | 0.628 | 0.4214 | -0.220 | 0.2701 | -1.911 | 0.4032 |
| 112E | 1.214 | 0.4013 | -0.150 | 0.2685 | -0.270 | 0.2211 |
| 112F | 1.440 | 0.5303 | -0.156 | 0.2693 | -0.709 | 0.3886 |
| 113 | -0.945 | 0.5898 | 0.210 | 0.1139 | 0.030 | 0.0756 |
| 115A | -1.915 | 0.5147 | 0.143 | 0.2338 | 0.239 | 0.2223 |
| 115B | 1.257 | 0.5134 | -0.109 | 0.2837 | -0.902 | 0.5995 |
| 115C | -0.622 | 1.0339 | 0.261 | 0.3310 | 0.575 | 0.2163 |
| 116O | -1.139 | 0.2752 | 0.223 | 0.2413 | 0.683 | 0.2482 |
| 117O | -1.917 | 0.3809 | 0.342 | 0.2534 | 0.186 | 0.0535 |
| 119 | -2.950 | 0.2729 | 0.378 | 0.2325 | -1.295 | 0.2882 |
| 119O | 0.675 | 0.1454 | -0.162 | 0.2358 | -1.185 | 0.5463 |
| 120 | -0.592 | 0.3880 | -0.070 | 0.2433 | -0.132 | 1.0910 |
| 120O | -0.848 | 0.1542 | 0.157 | 0.2292 | 0.508 | 0.2007 |
| 121 | 0.095 | 0.3778 | 0.187 | 0.2861 | 0.805 | 1.1015 |
| 122 | 0.751 | 0.2146 | -0.196 | 0.2527 | -1.092 | 0.8264 |
| 123 | -2.225 | 0.2033 | 0.471 | 0.2391 | 1.261 | 0.4525 |
| 124 | 1.465 | 0.4261 | -0.136 | 0.2741 | 0.375 | 0.3041 |
| 125 | 0.894 | 0.3010 | -0.116 | 0.2530 | 0.350 | 0.4134 |
| 125O | 1.628 | 0.2256 | -0.309 | 0.2409 | -0.504 | 0.6086 |
| 126 | 0.632 | 1.6015 | -0.065 | 0.3500 | -0.562 | 0.4912 |
| 127 | 2.302 | 0.4175 | -0.303 | 0.2784 | -0.070 | 0.3366 |
| 128 | -1.271 | 0.2139 | 0.015 | 0.2430 | -1.458 | 0.5431 |
| 129 | -2.015 | 0.3974 | 0.382 | 0.2390 | 0.208 | 0.1221 |
| 130 | 0.128 | 0.2824 | -0.072 | 0.2251 | -0.315 | 0.5686 |
| 131 | -0.240 | 0.2427 | -0.087 | 0.2447 | -0.421 | 0.9980 |
| 132 | -0.541 | 0.2336 | -0.097 | 0.2627 | 0.101 | 1.1228 |
| 133 | -0.760 | 0.1782 | 0.100 | 0.2478 | 0.705 | 0.9693 |
| 134 | 0.201 | 0.1968 | 0.010 | 0.2403 | 0.474 | 0.5706 |
| 135 | -0.272 | 0.3551 | 0.193 | 0.2649 | 0.912 | 0.3823 |
| 136 | -1.604 | 0.2316 | 0.287 | 0.2417 | 0.457 | 0.2940 |
| 137 | -2.403 | 0.4156 | 0.509 | 0.2524 | 0.894 | 0.4196 |
| 138 | 1.455 | 0.2848 | -0.215 | 0.2728 | 0.178 | 0.7602 |
| 139 | 1.616 | 0.1847 | -0.259 | 0.2418 | 0.194 | 0.7188 |
| 140 | 0.843 | 0.2163 | -0.178 | 0.2666 | 0.448 | 1.0875 |
| 141 | 0.245 | 0.2283 | -0.034 | 0.2609 | 0.150 | 0.7229 |
| 142 | 0.549 | 0.1850 | -0.065 | 0.2446 | 0.248 | 0.9004 |
| 143 | 1.732 | 0.1694 | -0.277 | 0.2475 | -0.064 | 1.0333 |
| 144 | 0.146 | 0.4002 | 0.059 | 0.2829 | -0.042 | 0.9467 |
| 145 | -0.324 | 0.2341 | 0.080 | 0.2523 | -0.042 | 0.8824 |
| 146 | -0.706 | 0.8816 | 0.231 | 0.1607 | 0.099 | 0.0978 |
| 147 | -1.315 | 0.9901 | 0.202 | 0.2738 | 0.091 | 0.7868 |

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|---|---|---|---|---|---|---|
| 148 | 0.569 | 1.7045 | 0.311 | 0.3475 | 0.236 | 0.1999 |
| 149 | 0.336 | 0.8525 | 0.078 | 0.2999 | 0.225 | 0.1511 |
| 150 | -1.529 | 1.0453 | 0.304 | 0.2658 | 0.229 | 0.2923 |
| 151 | -1.976 | 0.7234 | 0.229 | 0.2958 | 0.206 | 0.1852 |
| 152 | -0.755 | 0.4099 | 0.024 | 0.1447 | 0.010 | 0.1827 |
| 153 | -1.856 | 0.5506 | 0.273 | 0.2877 | 0.555 | 0.3258 |
| 154A | -2.818 | 0.9364 | 0.397 | 0.1179 | 0.109 | 0.0858 |
| 154B | -1.414 | 0.7143 | 0.265 | 0.1150 | 0.187 | 0.2828 |
| 155B | -1.270 | 0.6252 | 0.062 | 0.2762 | -0.141 | 0.3346 |
| 156 | -2.473 | 0.9763 | 0.277 | 0.2615 | -0.054 | 0.8052 |
| 157 | -0.949 | 0.4275 | 0.089 | 0.2649 | 0.449 | 0.3110 |
| 158 | -0.376 | 0.1655 | 0.063 | 0.2330 | -0.003 | 0.2659 |
| 158O | 1.235 | 0.1695 | -0.202 | 0.2398 | -0.058 | 0.4942 |
| 159 | -1.726 | 0.5251 | 0.279 | 0.2473 | 0.226 | 1.0781 |
| 160 | -0.907 | 0.2485 | 0.104 | 0.2457 | -0.062 | 0.2245 |
| 160O | -0.163 | 0.2583 | 0.052 | 0.2565 | 0.343 | 0.2689 |
| 161 | -1.391 | 0.2490 | 0.207 | 0.2179 | 0.464 | 0.4479 |
| 162 | -0.933 | 0.2177 | 0.151 | 0.2321 | 0.054 | 0.4392 |
| 162O | 0.732 | 0.2307 | -0.138 | 0.2476 | 0.148 | 0.2666 |
| 162P | -2.364 | 0.2897 | 0.428 | 0.2615 | 0.722 | 0.7259 |
| 163 | -1.771 | 0.3967 | 0.275 | 0.2467 | 0.733 | 0.8588 |
| 166N | 0.207 | 0.6083 | -0.144 | 0.3108 | -0.427 | 0.2898 |
| 167 | 1.488 | 0.3716 | -0.236 | 0.2815 | -0.277 | 0.3213 |
| 167O | -2.090 | 0.3978 | 0.265 | 0.2756 | -0.511 | 0.2073 |
| 168 | -2.987 | 0.4379 | 0.410 | 0.1283 | -0.369 | 0.3984 |
| 169 | -1.725 | 0.4352 | 0.279 | 0.2303 | 0.492 | 0.5113 |
| 169O | -0.616 | 0.1352 | 0.137 | 0.2199 | 0.319 | 0.2066 |
| 170 | -0.377 | 0.6163 | 0.136 | 0.1645 | 0.695 | 0.4719 |
| 171 | -0.484 | 0.4508 | 0.039 | 0.2665 | 0.241 | 0.1899 |
| 171O | -1.533 | 0.1954 | 0.269 | 0.2603 | -0.594 | 1.0272 |
| 172 | 1.343 | 0.3308 | -0.055 | 0.2035 | 0.974 | 0.6696 |
| 173 | -0.604 | 0.2415 | 0.099 | 0.2273 | -0.236 | 0.7430 |
| 174N | 1.146 | 0.3840 | -0.136 | 0.2763 | -0.047 | 0.5663 |
| 175N | -0.004 | 0.2545 | 0.030 | 0.2709 | 0.785 | 0.8996 |
| 179 | 0.513 | 0.3463 | -0.131 | 0.2761 | -0.393 | 1.0594 |
| 180 | -0.425 | 0.3210 | 0.122 | 0.2792 | -0.161 | 0.9245 |
| 181 | -0.384 | 0.2193 | -0.040 | 0.2622 | -1.310 | 0.8123 |
| 182 | 2.006 | 0.2908 | -0.304 | 0.2755 | -0.162 | 0.7569 |
| 183 | 2.332 | 0.1923 | -0.379 | 0.2542 | -0.049 | 0.9261 |
| 184A | -1.268 | 0.2762 | 0.389 | 0.2258 | 2.241 | 0.6186 |
| 184B | 0.583 | 0.1999 | -0.267 | 0.2432 | -0.533 | 1.0946 |
| 185 | -1.082 | 0.2632 | 0.157 | 0.2446 | 0.320 | 0.3022 |
| 186 | -2.348 | 0.2717 | 0.363 | 0.2523 | -0.028 | 0.3359 |
| 187A | -2.519 | 0.3601 | 0.443 | 0.2202 | 0.404 | 0.2452 |
| 187O | 0.878 | 0.1619 | -0.124 | 0.2368 | 0.676 | 0.6565 |
| 188 | 0.713 | 0.3856 | -0.071 | 0.2858 | -0.351 | 0.6214 |
| 189 | 0.719 | 0.2354 | -0.122 | 0.2605 | -0.248 | 0.5747 |
| 190 | -1.148 | 0.2549 | 0.162 | 0.2499 | 0.188 | 0.6053 |
| 191B | 0.594 | 0.8972 | 0.090 | 0.1566 | 0.280 | 0.1060 |
| 192 | -0.357 | 0.7850 | -0.218 | 0.2267 | -0.091 | 0.2113 |

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|---|---|---|---|---|---|---|
| 193 | -2.054 | 0.6123 | 0.352 | 0.2195 | 0.536 | 0.2071 |
| 194 | -1.282 | 0.4243 | 0.119 | 0.2185 | 0.148 | 0.2803 |
| 197 | -4.083 | 1.0528 | 0.562 | 0.2253 | 0.171 | 0.2991 |
| 200 | -2.732 | 0.4303 | 0.294 | 0.0611 | 0.274 | 0.1266 |
| 201 | -1.309 | 0.4864 | 0.101 | 0.1173 | -0.634 | 0.8590 |
| 202 | -0.026 | 0.4984 | -0.140 | 0.2821 | -0.126 | 1.0535 |
| 203 | 0.891 | 0.3989 | -0.022 | 0.2820 | -0.195 | 1.1192 |
| 204 | 0.738 | 0.4010 | -0.041 | 0.2663 | 0.000 | 1.0078 |
| 205 | -0.014 | 0.3740 | 0.022 | 0.1658 | 0.532 | 0.7020 |
| 206 | -1.111 | 0.3029 | 0.233 | 0.2624 | 0.664 | 0.5710 |
| 207 | 0.904 | 0.4599 | -0.126 | 0.3008 | -0.928 | 0.6623 |
| 208 | 0.717 | 0.2472 | -0.075 | 0.2671 | 0.594 | 0.7643 |
| 209C | -1.061 | 1.1742 | 0.329 | 0.3333 | -0.136 | 0.3240 |
| 209D | 1.594 | 0.7660 | -0.074 | 0.2941 | 0.135 | 0.0733 |
| 209E | 1.827 | 0.6091 | -0.108 | 0.2942 | 0.181 | 0.0812 |
| 209F | -1.576 | 1.0741 | 0.222 | 0.3461 | -0.352 | 0.4003 |
| 210A | -2.929 | 0.8031 | 0.456 | 0.1472 | 0.404 | 0.1145 |
| 210N | 1.215 | 0.8588 | 0.038 | 0.3341 | 0.290 | 0.5150 |
| 211A | -1.088 | 1.0624 | 0.121 | 0.2895 | 0.202 | 0.1187 |
| 211N | 0.729 | 0.4985 | -0.107 | 0.2836 | 0.660 | 0.4040 |
| 212 | -0.308 | 0.5612 | -0.266 | 0.2005 | -0.259 | 1.0755 |
| 212O | -2.289 | 0.2014 | 0.462 | 0.2365 | 0.269 | 0.4007 |
| 213 | -0.963 | 0.5952 | 0.087 | 0.1209 | 0.131 | 0.1017 |
| 214A | 0.530 | 0.7068 | -0.070 | 0.1332 | 0.221 | 0.1163 |
| 214B | -0.442 | 0.9298 | 0.111 | 0.1959 | 0.015 | 0.4069 |
| 214C | -0.175 | 0.6183 | 0.014 | 0.2994 | -0.190 | 0.2385 |
| 215B | -0.365 | 0.5648 | 0.079 | 0.2257 | 0.203 | 0.1078 |
| 215C | 0.974 | 0.4004 | -0.122 | 0.2731 | 0.023 | 0.4064 |
| 215O | -0.827 | 0.4257 | 0.099 | 0.2764 | -0.534 | 0.1426 |
| 216 | -2.400 | 0.7241 | 0.062 | 0.2410 | 0.292 | 0.3080 |
| 217 | -2.185 | 1.0516 | 0.397 | 0.1496 | 0.180 | 0.0566 |
| 218 | 0.705 | 0.8712 | -0.030 | 0.2746 | 0.354 | 0.3193 |
| 219 | 1.644 | 0.6903 | -0.141 | 0.3100 | 0.257 | 0.2625 |
| 220 | -0.925 | 0.4323 | 0.348 | 0.2716 | 0.561 | 0.3045 |
| 220O | -0.046 | 0.1856 | 0.052 | 0.2285 | 0.108 | 0.4070 |
| 221 | -1.068 | 0.7284 | 0.085 | 0.2226 | -0.278 | 0.4047 |
| 222 | -0.315 | 0.2148 | -0.066 | 0.2299 | -0.101 | 0.1614 |
| 222O | 0.841 | 0.2273 | -0.210 | 0.2497 | 0.640 | 0.3944 |
| 222P | -0.800 | 0.2011 | 0.800 | 0.2349 | 1.865 | 1.0724 |
| 223 | -0.484 | 0.6648 | 0.076 | 0.3345 | 0.504 | 0.6329 |
| 225 | -0.725 | 0.6148 | 0.181 | 0.3160 | 0.661 | 0.3921 |
| 225O | 0.741 | 0.1875 | -0.174 | 0.2315 | -0.240 | 0.2991 |
| 226 | -1.839 | 0.7574 | 0.270 | 0.3298 | 0.339 | 0.2301 |
| 227 | -0.274 | 0.3709 | 0.025 | 0.2686 | 0.568 | 0.2213 |
| 227O | 0.782 | 0.1628 | -0.145 | 0.2376 | -0.129 | 0.8824 |
| 228 | -1.084 | 0.4765 | 0.028 | 0.2348 | 0.082 | 0.2335 |
| 228O | -1.182 | 0.2140 | 0.208 | 0.2606 | 0.218 | 1.0888 |
| 229 | -0.847 | 0.3268 | 0.223 | 0.2391 | 0.652 | 0.1348 |
| 229O | 1.351 | 0.1595 | -0.227 | 0.2366 | -0.146 | 0.8440 |
| 230 | -1.880 | 0.2455 | 0.038 | 0.2512 | -1.936 | 0.7538 |

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|---|---|---|---|---|---|---|
| 230O | -1.808 | 0.2409 | 0.240 | 0.2459 | 0.655 | 0.2013 |
| 231 | -1.390 | 0.1581 | 0.211 | 0.2288 | -0.030 | 0.1307 |
| 231O | 1.410 | 0.1580 | -0.258 | 0.2521 | 0.101 | 1.0911 |
| 232 | -1.518 | 0.5120 | -0.027 | 0.2280 | -0.029 | 0.3256 |
| 232O | -1.198 | 0.1786 | 0.249 | 0.2550 | 0.289 | 1.0450 |
| 233 | -1.610 | 0.6453 | 0.147 | 0.1610 | -0.063 | 0.1686 |
| 234 | -1.432 | 0.4264 | 0.144 | 0.2057 | 0.056 | 0.1332 |
| 234O | -1.290 | 0.1907 | 0.283 | 0.2327 | 0.922 | 0.4030 |
| 235 | -2.630 | 0.3303 | 0.625 | 0.2510 | 1.533 | 0.4141 |
| 236 | -0.004 | 0.2783 | 0.034 | 0.2593 | 0.371 | 0.4360 |
| 237 | -2.774 | 0.2547 | 0.587 | 0.2372 | 1.053 | 0.5194 |
| 238 | -2.053 | 0.4853 | 0.545 | 0.1986 | 0.973 | 0.8955 |
| 239 | 0.387 | 0.4380 | 0.023 | 0.2635 | 0.545 | 0.5369 |
| 240N | -0.451 | 0.4336 | 0.101 | 0.2346 | -0.295 | 0.5475 |
| 241N | -0.856 | 0.3257 | 0.251 | 0.2800 | 0.335 | 1.0614 |
| 242A | -1.521 | 0.8161 | 0.367 | 0.2443 | 0.701 | 0.4991 |
| 242B | -0.643 | 0.2848 | -0.163 | 0.2222 | -0.412 | 1.0860 |
| 242C | -0.678 | 0.2484 | 0.016 | 0.2592 | -1.168 | 1.0124 |
| 242D | -1.558 | 0.2768 | 0.286 | 0.2598 | 0.732 | 0.7271 |
| 242E | -2.848 | 0.3832 | 0.436 | 0.2817 | -0.328 | 0.8400 |
| 242F | -1.905 | 0.2122 | 0.012 | 0.2503 | 0.568 | 1.0835 |
| 243 | 1.798 | 0.2549 | -0.250 | 0.2612 | -0.003 | 0.7914 |
| 244 | -2.604 | 0.3150 | 0.277 | 0.2271 | 0.467 | 0.7707 |
| 245 | -2.381 | 0.2794 | 0.347 | 0.2728 | -0.011 | 0.9891 |
| 247 | 0.364 | 0.1635 | 0.114 | 0.1983 | -0.011 | 1.0729 |
| 248 | -0.174 | 0.3057 | 0.063 | 0.2753 | 0.775 | 0.9992 |
| 249 | -0.274 | 0.3635 | 0.099 | 0.2761 | 0.474 | 0.3351 |
| 250 | -2.358 | 0.2524 | 0.432 | 0.2705 | 0.965 | 0.9937 |
| 251 | -1.257 | 0.1900 | 0.384 | 0.2456 | 1.649 | 0.5492 |
| 252 | -1.624 | 0.2323 | 0.302 | 0.2568 | 0.765 | 0.4513 |
| 253 | -0.799 | 0.2767 | 0.170 | 0.2585 | -0.198 | 0.5031 |
| 254 | 0.091 | 0.2104 | 0.053 | 0.2563 | 0.609 | 0.6771 |
| 255 | -1.465 | 0.2345 | 0.194 | 0.2637 | 0.833 | 0.5912 |
| 256 | -1.029 | 0.2855 | 0.250 | 0.2567 | 2.177 | 0.4887 |
| 257 | -1.638 | 0.4956 | 0.294 | 0.2840 | 1.455 | 0.6483 |
| 258 | -1.252 | 0.4198 | 0.201 | 0.2770 | 0.644 | 0.4310 |
| 258O | -2.034 | 0.3741 | 0.376 | 0.2850 | 0.222 | 0.9422 |
| 259 | -1.594 | 0.2954 | 0.243 | 0.2504 | 0.109 | 1.0930 |
| 260 | -0.715 | 0.2752 | 0.176 | 0.2719 | 1.242 | 0.9667 |
| 260O | 0.182 | 0.2644 | -0.044 | 0.2523 | -0.784 | 0.2495 |
| 261 | -1.470 | 0.2461 | 0.331 | 0.2300 | 0.363 | 0.2350 |
| 261O | -0.543 | 0.2614 | 0.258 | 0.2586 | -0.188 | 0.8875 |
| 262O | -0.861 | 0.1700 | 0.157 | 0.2529 | -0.134 | 1.0737 |
| 263 | -1.180 | 0.8952 | 0.187 | 0.1767 | 0.086 | 0.1369 |
| 265 | -1.391 | 0.6969 | 0.131 | 0.2708 | -0.316 | 0.2300 |
| 266 | -1.489 | 0.2237 | 0.277 | 0.2315 | 0.409 | 0.1359 |
| 266O | 0.445 | 0.1625 | 0.179 | 0.2500 | 1.508 | 1.0927 |
| 267 | -2.191 | 0.1908 | 0.265 | 0.2332 | -0.746 | 0.5117 |
| 267O | -1.219 | 0.1879 | 0.245 | 0.2466 | 0.692 | 0.4820 |
| 268 | -1.043 | 0.4859 | 0.176 | 0.2364 | 0.065 | 0.1326 |

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|---|---|---|---|---|---|---|
| 268O | 0.250 | 0.1455 | -0.101 | 0.2136 | -0.490 | 0.2959 |
| 269 | -0.777 | 0.6424 | 0.162 | 0.2406 | 0.296 | 0.1453 |
| 270 | -1.031 | 0.3516 | 0.256 | 0.2732 | 0.843 | 0.2617 |
| 270O | -0.020 | 0.1401 | -0.025 | 0.2323 | -0.176 | 0.7298 |
| 271 | -1.190 | 0.3537 | 0.468 | 0.1967 | 0.567 | 0.3218 |
| 272 | -1.911 | 0.4512 | 0.640 | 0.2355 | 0.858 | 1.0354 |
| 273 | -2.196 | 0.3858 | 0.391 | 0.2237 | 0.953 | 0.8918 |
| 274 | -0.357 | 0.3872 | -0.136 | 0.2539 | -0.852 | 1.0189 |
| 275 | -2.053 | 0.2628 | 0.345 | 0.2045 | 0.598 | 0.7870 |
| 276 | -2.442 | 0.2566 | 0.476 | 0.2400 | 1.440 | 0.3694 |
| 277 | 0.944 | 0.4466 | -0.142 | 0.2925 | -0.391 | 0.5372 |
| 278 | 0.481 | 0.2609 | -0.024 | 0.2567 | 0.883 | 0.6315 |
| 279 | -1.562 | 0.2848 | 0.076 | 0.2258 | -0.691 | 1.0305 |
| 280 | -0.613 | 0.2389 | 0.031 | 0.2560 | -0.432 | 0.5515 |
| 281 | 0.212 | 0.1884 | -0.037 | 0.2453 | -0.012 | 0.6298 |
| 282 | -1.469 | 0.2043 | 0.288 | 0.2610 | 0.338 | 0.8582 |
| 283 | -0.935 | 0.3777 | 0.262 | 0.2367 | 0.318 | 0.8741 |
| 284 | -0.313 | 0.3013 | 0.038 | 0.2622 | 0.335 | 0.8207 |
| 286 | -1.005 | 0.9629 | 0.149 | 0.3355 | 0.323 | 0.2738 |
| 288A | -0.138 | 0.3673 | 0.268 | 0.2624 | 1.535 | 0.3577 |
| 289 | -1.030 | 0.3886 | 0.203 | 0.2735 | -0.058 | 1.0479 |
| 290 | -0.155 | 0.4492 | 0.089 | 0.2645 | -0.092 | 0.5183 |
| 295 | 0.401 | 0.3873 | -0.142 | 0.2148 | -0.378 | 0.8975 |
| 296 | 1.291 | 0.3631 | -0.188 | 0.2775 | -0.024 | 0.3391 |
| 297 | 0.080 | 0.2344 | 0.022 | 0.2558 | 0.115 | 0.3935 |
| 298 | -0.645 | 0.3061 | 0.209 | 0.2617 | 1.323 | 0.5084 |
| 299 | -1.859 | 0.3303 | 0.335 | 0.2153 | 0.402 | 0.3184 |
| 300 | -0.129 | 0.4600 | -0.140 | 0.2982 | -0.483 | 0.7306 |
| 301 | -0.726 | 0.2648 | 0.141 | 0.2734 | 0.492 | 0.9745 |
| 303 | 0.289 | 0.7235 | 0.060 | 0.1995 | 0.752 | 0.4913 |
| 304 | -1.232 | 0.7088 | 0.126 | 0.2131 | 0.295 | 0.6062 |
| 305 | -0.281 | 0.8386 | -0.223 | 0.3296 | -0.546 | 0.8545 |
| 308 | -1.057 | 0.3386 | 0.127 | 0.2699 | 0.083 | 0.4110 |
| 309 | -1.272 | 0.1986 | 0.132 | 0.2361 | -0.555 | 0.2268 |
| 309O | 0.130 | 0.2064 | 0.005 | 0.2473 | 1.182 | 0.4553 |
| 310 | 0.246 | 0.3009 | 0.027 | 0.2582 | 0.165 | 1.0317 |
| 311 | 0.621 | 0.2684 | -0.068 | 0.2663 | 0.515 | 0.7461 |
| 311O | 0.188 | 0.2584 | -0.073 | 0.2510 | -0.688 | 0.1662 |
| 312 | -2.078 | 0.5041 | 0.348 | 0.2680 | 0.407 | 0.4282 |
| 313 | -2.400 | 0.2553 | 0.439 | 0.2570 | 0.533 | 0.8710 |
| 314O | -1.515 | 0.1816 | 0.213 | 0.2289 | -0.151 | 0.2655 |
| 315 | -0.900 | 0.4726 | 0.275 | 0.2302 | 0.874 | 0.4004 |
| 315O | -1.511 | 0.1756 | 0.299 | 0.2295 | 0.469 | 0.2197 |
| 316 | 1.546 | 0.3954 | -0.077 | 0.2409 | -0.116 | 0.3556 |
| 317 | -1.817 | 0.2602 | 0.326 | 0.2464 | 0.294 | 1.1065 |
| 317O | 4.637 | 0.1340 | -0.840 | 0.2421 | -0.808 | 1.0778 |
| 318 | 0.018 | 0.3587 | -0.140 | 0.2456 | -0.237 | 0.3794 |
| 319 | -1.688 | 0.2595 | 0.355 | 0.2574 | 1.715 | 0.9987 |
| 320 | 2.425 | 0.4018 | -0.357 | 0.2967 | -0.836 | 0.8137 |
| 321 | 1.065 | 0.2630 | -0.192 | 0.2716 | -0.286 | 1.0124 |

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|---|---|---|---|---|---|---|
| 322 | -0.654 | 0.3303 | 0.110 | 0.2513 | -0.033 | 0.8767 |
| 323 | -0.078 | 0.2873 | -0.015 | 0.2771 | 0.113 | 1.0506 |
| 323O | -1.091 | 0.1740 | -0.100 | 0.2334 | -1.972 | 0.8890 |
| 324 | 0.189 | 0.2082 | -0.002 | 0.2569 | 0.435 | 0.6751 |
| 325 | -0.305 | 0.2486 | 0.122 | 0.2596 | -0.199 | 0.6620 |
| 326 | -0.586 | 0.2114 | 0.100 | 0.2655 | 0.436 | 0.9586 |
| 327 | -2.850 | 0.3318 | 0.482 | 0.2619 | 0.423 | 1.1009 |
| 331 | -0.355 | 0.2856 | 0.099 | 0.2346 | 0.288 | 0.5426 |
| 332 | -1.183 | 0.2495 | 0.334 | 0.2629 | 1.229 | 0.9547 |
| 333 | -2.146 | 0.3594 | 0.431 | 0.2661 | 0.426 | 1.1109 |
| 334 | -0.772 | 0.6689 | 0.072 | 0.2648 | 0.037 | 0.1768 |
| 335 | -0.065 | 0.6647 | 0.193 | 0.2951 | -0.431 | 0.4505 |
| 336 | -0.939 | 0.3739 | 0.276 | 0.2836 | 1.628 | 0.5768 |
| 337 | -0.179 | 0.3026 | 0.059 | 0.2622 | 0.095 | 0.4109 |
| 338 | -2.245 | 0.3627 | 0.449 | 0.2896 | 1.519 | 1.0427 |
| 339 | -1.925 | 0.3059 | 0.277 | 0.2377 | 0.732 | 0.5179 |
| 340 | -1.989 | 0.2061 | 0.235 | 0.2307 | -0.333 | 0.6213 |
| 340O | -0.088 | 0.2064 | 0.024 | 0.2550 | -0.301 | 0.5751 |
| 341 | -1.560 | 0.5052 | 0.224 | 0.2683 | 0.355 | 0.2883 |
| 341O | -1.151 | 0.1508 | 0.110 | 0.2227 | -0.632 | 0.5423 |
| 343O | 0.230 | 0.1590 | -0.063 | 0.2503 | 0.160 | 1.1011 |
| 345 | -2.460 | 0.4037 | 0.538 | 0.2637 | 0.776 | 1.0910 |
| 345O | -2.067 | 0.2631 | 0.245 | 0.2242 | -0.728 | 0.4139 |
| 346 | -0.105 | 0.3412 | -0.003 | 0.2229 | -0.661 | 1.0540 |
| 347 | -2.234 | 0.2712 | 0.304 | 0.2000 | -0.587 | 0.2896 |
| 348 | -2.282 | 0.3157 | 0.326 | 0.2227 | 0.161 | 0.3266 |
| 350 | -0.933 | 0.2631 | 0.119 | 0.2726 | 0.401 | 1.0504 |
| 352 | -2.350 | 0.2175 | 0.434 | 0.2373 | 1.440 | 0.6536 |
| 353 | -1.022 | 0.4690 | 0.208 | 0.0962 | -0.167 | 0.3605 |
| 354 | -2.353 | 0.7896 | 0.421 | 0.2888 | 0.392 | 0.2215 |
| 355 | -0.821 | 0.3976 | -0.004 | 0.2018 | -0.021 | 0.2360 |
| 355O | -2.837 | 0.3273 | 0.466 | 0.2366 | 0.130 | 0.3494 |
| 356 | 0.405 | 0.3133 | -0.163 | 0.2574 | -0.120 | 0.1464 |
| 356O | -0.584 | 0.3360 | 0.064 | 0.2689 | -0.419 | 0.4166 |
| 357 | -1.193 | 0.5373 | 0.210 | 0.1676 | 0.368 | 0.9257 |
| 358 | -0.399 | 0.4062 | -0.074 | 0.1825 | 0.195 | 0.8054 |
| 359 | 0.837 | 0.1845 | 0.119 | 0.1485 | 1.195 | 0.6482 |
| 359O | 1.568 | 0.1952 | -0.140 | 0.1791 | 0.219 | 0.4755 |
| 360 | -1.465 | 0.3102 | -0.074 | 0.2153 | 0.323 | 0.1600 |
| 360O | 0.142 | 0.1404 | -0.050 | 0.2246 | -0.195 | 0.5160 |
| 361 | -1.909 | 0.3627 | 0.204 | 0.2582 | 0.055 | 0.3194 |
| 361O | -1.271 | 0.2096 | 0.118 | 0.2534 | 0.236 | 1.0818 |
| 364 | -2.111 | 0.1507 | 0.319 | 0.2236 | -0.309 | 0.2132 |
| 364O | 2.082 | 0.1350 | -0.366 | 0.2287 | -0.236 | 0.6007 |
| 365 | -1.803 | 0.5417 | 0.207 | 0.2698 | 0.135 | 0.3471 |
| 365O | -1.682 | 0.2054 | 0.269 | 0.2371 | 0.476 | 1.0891 |
| 366 | 0.071 | 0.3924 | 0.057 | 0.2409 | 0.641 | 0.3754 |
| 367 | -1.278 | 0.2261 | 0.086 | 0.1697 | -0.157 | 0.4168 |
| 368 | -1.788 | 0.2850 | 0.452 | 0.2619 | 0.577 | 0.5759 |
| 369 | -0.333 | 0.2162 | 0.078 | 0.2536 | -0.029 | 1.0934 |

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|---|---|---|---|---|---|---|
| 370 | 1.368 | 0.4978 | -0.133 | 0.2493 | 0.294 | 0.2356 |
| 371 | 1.364 | 0.4217 | -0.231 | 0.2878 | -0.447 | 1.0067 |
| 372 | 2.366 | 0.2845 | -0.395 | 0.2702 | -0.717 | 0.9389 |
| 373 | 3.024 | 0.2109 | -0.478 | 0.2607 | -0.070 | 0.9757 |
| 373O | -1.166 | 0.1369 | 0.179 | 0.2431 | 0.115 | 1.1097 |
| 374 | -0.722 | 0.4160 | 0.126 | 0.2765 | 0.022 | 0.2345 |
| 375 | -2.339 | 0.3136 | 0.501 | 0.2063 | 0.614 | 0.8587 |
| 376 | -0.287 | 0.2349 | 0.045 | 0.2594 | -0.391 | 0.9313 |
| 377N | -1.391 | 0.2666 | 0.191 | 0.2076 | 0.178 | 0.1848 |
| 377O | -1.921 | 0.1948 | 0.300 | 0.2387 | 0.177 | 0.8721 |
| 378N | -1.243 | 0.3459 | 0.156 | 0.2651 | -0.139 | 0.3896 |
| 379 | -0.707 | 0.2061 | 0.228 | 0.2458 | 0.898 | 0.9515 |
| 380 | -0.479 | 0.1702 | 0.034 | 0.2546 | 0.400 | 1.1064 |
| 381 | -0.653 | 0.1580 | 0.079 | 0.2171 | -0.123 | 0.3347 |
| 381O | 0.240 | 0.1556 | -0.302 | 0.2266 | -0.315 | 1.1130 |
| 382 | -1.433 | 0.1691 | 0.278 | 0.2515 | 1.442 | 0.9798 |
| 383 | 0.188 | 0.2310 | -0.054 | 0.2661 | -0.371 | 1.1059 |
| 384 | -0.029 | 0.1787 | 0.065 | 0.2500 | 0.710 | 0.9674 |
| 385A | -2.278 | 0.2840 | 0.401 | 0.1984 | 0.713 | 1.0777 |
| 385B | -0.681 | 0.3968 | 0.168 | 0.2719 | 0.717 | 1.0732 |
| 385C | -1.825 | 0.6143 | 0.217 | 0.0481 | -0.275 | 0.2379 |
| 386N | -1.343 | 0.9451 | 0.254 | 0.0357 | 0.210 | 0.0305 |
| 387N | -2.066 | 0.9945 | 0.288 | 0.0572 | 0.074 | 0.3433 |
| 388A | -0.563 | 0.5888 | 0.114 | 0.0546 | 0.548 | 0.1698 |
| 388B | 0.521 | 0.5985 | 0.160 | 0.2100 | 0.137 | 0.0884 |
| 388C | -2.275 | 0.6082 | 0.347 | 0.0613 | 0.015 | 0.2613 |
| 389A | -0.783 | 1.2072 | 0.163 | 0.1005 | 0.169 | 0.0493 |
| 389B | -0.966 | 0.7195 | 0.190 | 0.1631 | -0.166 | 0.7630 |
| 390 | 1.734 | 0.3042 | -0.239 | 0.2624 | 0.218 | 0.1801 |
| 391 | 3.336 | 0.1854 | -0.503 | 0.2330 | -0.027 | 0.7062 |
| 391O | -1.046 | 0.1346 | 0.262 | 0.2433 | 0.334 | 1.1131 |
| 394 | -2.346 | 0.6367 | 0.397 | 0.3066 | 0.036 | 0.3495 |
| 394O | -1.647 | 0.1658 | 0.432 | 0.2213 | 1.145 | 0.8027 |
| 395 | 1.197 | 0.2784 | -0.070 | 0.2420 | 0.512 | 0.4989 |
| 396 | -2.666 | 0.4899 | 0.571 | 0.2839 | 1.072 | 0.2424 |
| 397 | -0.881 | 0.3123 | 0.367 | 0.2606 | 1.706 | 0.7364 |
| 398 | -0.427 | 0.2958 | -0.205 | 0.2112 | -1.156 | 0.1784 |
| 399 | -0.928 | 0.2663 | 0.041 | 0.2556 | -1.033 | 0.6107 |
| 400 | -0.319 | 0.6467 | -0.156 | 0.1954 | -0.318 | 0.5818 |
| 401 | -2.110 | 0.8880 | 0.199 | 0.2139 | 0.178 | 0.2862 |
| 402 | -2.228 | 0.5334 | 0.457 | 0.2570 | 0.110 | 0.2471 |
| 402O | -2.381 | 0.2248 | 0.303 | 0.2264 | -0.379 | 0.5658 |
| 403 | 1.464 | 0.7594 | -0.189 | 0.3491 | -0.115 | 1.1412 |
| 404 | 0.151 | 0.3677 | 0.047 | 0.2456 | 0.295 | 0.3601 |
| 405 | -1.023 | 0.6458 | 0.159 | 0.2337 | -0.277 | 0.4157 |
| 408O | -2.048 | 0.1917 | 0.284 | 0.2281 | -0.039 | 0.4148 |
| 410X | -0.101 | 0.1918 | 0.654 | 0.2039 | 1.662 | 0.9133 |
| 413 | -0.730 | 0.3029 | -0.022 | 0.1450 | -0.904 | 0.6399 |
| 414 | -1.486 | 0.2582 | -0.011 | 0.1925 | 1.817 | 0.9039 |
| 415 | 0.244 | 1.3226 | 0.129 | 0.2965 | 0.386 | 0.1851 |

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|---|---|---|---|---|---|---|
| 415O | -1.923 | 0.1596 | 0.213 | 0.2218 | -0.206 | 0.2143 |
| 416N | 1.221 | 0.8168 | -0.261 | 0.3279 | 0.532 | 0.6357 |
| 417N | -2.276 | 0.5569 | 0.185 | 0.1647 | 0.577 | 0.3217 |
| 418 | 0.874 | 0.3665 | -0.120 | 0.2600 | 0.393 | 0.2227 |
| 419 | -1.543 | 0.2603 | 0.436 | 0.1927 | -2.224 | 0.9151 |
| 420 | -2.090 | 0.2455 | 0.411 | 0.2674 | -0.878 | 1.0453 |
| 421 | -0.470 | 0.2720 | 0.104 | 0.2758 | 0.247 | 1.1250 |
| 422 | -0.799 | 0.2306 | -0.055 | 0.2361 | -1.628 | 0.5282 |
| 423 | 1.037 | 0.4625 | -0.085 | 0.2945 | -0.229 | 1.0732 |
| 426C | -3.295 | 0.3884 | 0.679 | 0.2686 | 1.848 | 0.8252 |
| 426D | -2.449 | 0.2788 | 0.372 | 0.2579 | -0.061 | 0.5933 |
| 427A | -1.999 | 0.2489 | 0.452 | 0.2547 | 1.489 | 0.4884 |
| 427D | -1.444 | 0.2491 | 0.267 | 0.2547 | 0.537 | 0.4896 |
| 429A | -0.183 | 0.3538 | 0.148 | 0.2741 | -0.202 | 0.4759 |
| 429B | -1.104 | 0.2732 | 0.206 | 0.2675 | -0.475 | 0.6027 |
| 430D | -2.893 | 0.3916 | 0.393 | 0.2690 | -0.595 | 0.8296 |
| 431A | -2.072 | 0.3528 | 0.371 | 0.2654 | 0.597 | 0.7690 |
| 431B | -2.092 | 0.2606 | 0.446 | 0.2560 | 1.314 | 0.5368 |
| 432A | -0.961 | 0.2727 | -0.213 | 0.1186 | 0.586 | 0.3031 |
| 432C | -1.530 | 0.2431 | 0.260 | 0.2540 | 0.333 | 0.4626 |
| 436A | -0.093 | 0.2354 | 0.063 | 0.2546 | 0.296 | 0.7896 |
| 436B | 0.601 | 0.1844 | -0.146 | 0.2560 | -0.635 | 0.9550 |
| 436C | -1.758 | 0.2604 | 0.196 | 0.2559 | -0.651 | 0.5320 |
| 439 | -0.459 | 1.4762 | -0.123 | 0.3186 | 0.221 | 0.1016 |
| 439O | -3.322 | 0.3303 | 0.607 | 0.2546 | 0.481 | 1.0920 |
| 441A | -1.628 | 0.4751 | 0.096 | 0.2584 | 0.238 | 0.2757 |
| 441O | -1.868 | 0.1633 | 0.303 | 0.2333 | 0.855 | 0.6893 |
| 442 | -1.170 | 1.1681 | 0.321 | 0.2110 | 0.180 | 0.0588 |
| 442O | -2.579 | 0.3151 | 0.393 | 0.2327 | 0.281 | 0.3055 |
| 443 | -3.052 | 0.3651 | 0.746 | 0.1671 | 0.062 | 0.1909 |
| 443O | -0.943 | 0.1514 | 0.160 | 0.2299 | 0.103 | 0.3130 |
| 444 | -0.985 | 0.3284 | -0.177 | 0.2509 | -1.514 | 0.4347 |
| 445 | -1.197 | 0.2374 | 0.192 | 0.2674 | -0.189 | 0.7877 |
| 446 | -2.929 | 0.2500 | 0.769 | 0.2338 | 0.662 | 1.1182 |
| 447 | -0.861 | 0.1834 | 0.275 | 0.2533 | 0.409 | 1.1048 |
| 448 | -2.000 | 0.1804 | 0.381 | 0.2436 | 0.298 | 0.8969 |
| 449 | -0.144 | 0.2486 | 0.119 | 0.2428 | -0.162 | 0.9675 |
| 450 | -0.208 | 0.1954 | 0.075 | 0.2367 | -0.356 | 0.5014 |
| 451 | -1.522 | 0.2007 | 0.647 | 0.2520 | -0.208 | 1.0112 |
| 452A | -0.220 | 0.5892 | 0.028 | 0.3049 | 0.299 | 0.1771 |
| 452B | 0.240 | 0.3684 | 0.004 | 0.2808 | -0.080 | 0.6497 |
| 453A | -1.911 | 0.3869 | 0.254 | 0.2613 | -0.694 | 0.2854 |
| 453B | -0.344 | 0.2161 | 0.216 | 0.2611 | 1.721 | 0.8201 |
| 454 | -2.173 | 0.3461 | 0.561 | 0.2653 | 0.624 | 0.5420 |
| 455 | -0.515 | 0.1695 | -0.184 | 0.2404 | -1.431 | 1.0365 |
| 458 | -2.877 | 0.4696 | 0.409 | 0.0917 | -0.026 | 0.0785 |
| 459 | -2.089 | 0.3172 | 0.406 | 0.1339 | 0.276 | 0.9205 |
| 459O | -1.616 | 0.1654 | 0.287 | 0.2227 | 0.300 | 0.2043 |
| 460 | -2.027 | 0.2257 | 0.326 | 0.2131 | 0.228 | 0.3890 |
| 461 | -2.773 | 0.3854 | 0.630 | 0.1865 | 0.718 | 0.1948 |

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|---|---|---|---|---|---|---|
| 461O | -1.173 | 0.1557 | 0.145 | 0.2241 | -0.641 | 0.2455 |
| 463 | -0.919 | 0.2782 | 0.405 | 0.2613 | 1.013 | 1.0706 |
| 464 | -0.654 | 0.2164 | 0.174 | 0.2592 | 0.167 | 1.0895 |
| 465 | -2.194 | 0.3313 | 0.553 | 0.1316 | 3.465 | 0.2373 |
| 466 | -0.633 | 0.2799 | 0.431 | 0.2331 | 1.879 | 0.4280 |
| 467 | 0.017 | 0.1908 | 0.296 | 0.2392 | 3.130 | 0.7256 |
| 468 | -0.809 | 1.0387 | 0.027 | 0.2356 | 0.305 | 0.2444 |
| 471N | -0.378 | 0.9250 | -0.002 | 0.2745 | 0.412 | 0.2834 |
| 473 | -0.455 | 0.3760 | 0.179 | 0.1035 | 0.291 | 0.1696 |
| 475A | 0.164 | 0.5224 | 0.188 | 0.0646 | 0.206 | 0.0270 |
| 475B | 2.933 | 0.9785 | -0.365 | 0.3477 | 0.251 | 0.2244 |
| 475O | -1.987 | 0.2605 | 0.088 | 0.2437 | -0.770 | 1.1036 |
| 477 | -1.383 | 0.7473 | 0.584 | 0.2744 | -0.177 | 0.1522 |
| 477O | -0.818 | 0.1556 | 0.153 | 0.2270 | 0.323 | 0.2696 |
| 478 | 0.657 | 0.7458 | 0.023 | 0.3014 | -0.093 | 1.0610 |
| 479 | -0.316 | 0.4646 | 0.011 | 0.2734 | -0.579 | 0.4882 |
| 479O | -1.061 | 0.2340 | 0.195 | 0.2409 | 0.544 | 0.3724 |
| 481A | -0.021 | 1.5062 | 0.109 | 0.2694 | 0.301 | 0.2988 |
| 482 | -1.491 | 0.5703 | 0.257 | 0.0437 | 0.184 | 0.0839 |
| 483 | -1.098 | 0.5060 | 0.282 | 0.0180 | 0.183 | 0.0161 |
| 483B | -1.772 | 0.7584 | 0.306 | 0.0543 | 0.183 | 0.0504 |
| 486 | -1.562 | 0.6031 | 0.229 | 0.0786 | 0.339 | 0.7985 |
| 487 | -1.395 | 0.6253 | 0.279 | 0.2410 | 0.060 | 0.2399 |
| 491 | -0.431 | 1.0496 | 0.087 | 0.3431 | 0.318 | 0.0718 |
| 493 | 0.206 | 0.5739 | 0.265 | 0.2620 | 0.976 | 0.5436 |
| 494 | 0.829 | 0.3034 | -0.044 | 0.2517 | 0.387 | 0.2957 |
| 494O | 0.397 | 0.3260 | 0.001 | 0.2694 | -0.282 | 0.3466 |
| 501A | -1.937 | 0.5754 | 0.194 | 0.1271 | -0.293 | 0.2688 |
| 501B | -2.208 | 0.5536 | 0.372 | 0.2850 | 1.094 | 1.0249 |
| 501O | -1.480 | 0.2441 | 0.086 | 0.2421 | -0.386 | 0.1270 |
| 502 | -0.584 | 0.7402 | -0.025 | 0.2440 | -0.830 | 0.4394 |
| 509O | -2.181 | 0.2106 | 0.102 | 0.2143 | -0.993 | 0.3890 |
| 520 | -0.921 | 0.1630 | -0.029 | 0.2358 | -2.082 | 0.8083 |
| 521O | -1.329 | 0.3056 | 0.018 | 0.2362 | -1.335 | 0.8439 |
| 570 | -0.139 | 0.9860 | 0.000 | 0.3128 | -0.627 | 0.3742 |
| 570O | -0.628 | 0.3738 | 0.166 | 0.1304 | 0.326 | 0.0583 |
| 701O | 2.612 | 0.1301 | -0.472 | 0.2401 | -0.422 | 1.1124 |
| 702O | 0.729 | 0.1378 | -0.129 | 0.2426 | -0.324 | 1.0801 |
| 704O | -2.241 | 0.1520 | 0.405 | 0.2409 | 0.361 | 1.1112 |
| 706O | -0.093 | 0.1357 | 0.007 | 0.2413 | -0.577 | 0.9851 |
| 707O | -0.672 | 0.1468 | -0.030 | 0.2348 | -1.460 | 0.8139 |
| 707P | 0.747 | 0.1303 | -0.130 | 0.2401 | -0.078 | 1.1070 |
| 709O | -1.236 | 0.1396 | 0.212 | 0.2412 | 0.079 | 1.0696 |
| 710O | 3.304 | 0.1317 | -0.596 | 0.2415 | -0.531 | 1.1130 |
| 711O | 3.242 | 0.1319 | -0.565 | 0.2407 | -0.279 | 1.0771 |
| 712O | 0.995 | 0.1313 | -0.191 | 0.2408 | -0.229 | 1.1092 |
| 713O | -2.040 | 0.1985 | 0.342 | 0.2506 | -0.721 | 1.0865 |
| 714O | -1.352 | 0.1767 | 0.262 | 0.2462 | 0.284 | 1.1132 |
| 715O | -2.205 | 0.2179 | 0.258 | 0.2427 | -1.124 | 1.0186 |
| 716O | -0.069 | 0.1553 | -0.093 | 0.2309 | -1.057 | 0.2944 |

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|---|---|---|---|---|---|---|
| 717O | -0.585 | 0.1362 | 0.126 | 0.2396 | 0.297 | 1.0235 |
| 718O | 2.852 | 0.1305 | -0.515 | 0.2405 | -0.450 | 1.1122 |
| 719O | 0.162 | 0.1330 | 0.005 | 0.2397 | -0.105 | 1.0449 |
| 720O | 0.538 | 0.1350 | -0.091 | 0.2430 | -0.082 | 1.1117 |
| 801H | 1.974 | 0.1663 | -0.328 | 0.2426 | -0.223 | 0.9704 |
| 801J | -0.086 | 0.1467 | 0.077 | 0.2381 | 0.745 | 1.0425 |
| 801R | 0.472 | 0.1434 | -0.129 | 0.2393 | -0.900 | 1.0275 |
| 801T | -0.426 | 0.1610 | 0.020 | 0.2402 | -0.522 | 1.0891 |
| 801U | -0.148 | 0.1594 | -0.130 | 0.2415 | -2.169 | 0.6977 |
| 801W | 2.206 | 0.1332 | -0.364 | 0.2425 | -0.134 | 1.1108 |
| 802P | 4.438 | 0.1303 | -0.811 | 0.2403 | -0.833 | 1.1104 |
| 802U | 3.276 | 0.1357 | -0.557 | 0.2421 | -0.559 | 1.1131 |
| 803N | 2.086 | 0.1308 | -0.365 | 0.2406 | -0.172 | 1.1039 |
| 803R | 2.076 | 0.1299 | -0.372 | 0.2398 | -0.245 | 1.1111 |
| 803T | -1.298 | 0.2295 | 0.201 | 0.2505 | 0.021 | 1.1095 |
| 803U | 4.257 | 0.1299 | -0.768 | 0.2398 | -0.683 | 1.1122 |
| 804P | -0.226 | 0.1404 | 0.042 | 0.2427 | -0.270 | 1.0945 |
| 804R | 1.851 | 0.1313 | -0.348 | 0.2410 | -0.386 | 1.1107 |
| 805P | 1.188 | 0.1386 | -0.214 | 0.2336 | -0.219 | 0.7131 |
| 806H | 2.970 | 0.1514 | -0.516 | 0.2476 | -0.364 | 1.1029 |
| 806P | -0.217 | 0.1370 | 0.112 | 0.2394 | 0.569 | 1.0987 |
| 806R | 0.925 | 0.1336 | -0.218 | 0.2396 | -1.221 | 1.0752 |
| 807P | -1.285 | 0.1516 | 0.233 | 0.2366 | 0.056 | 0.8320 |
| 808H | 1.950 | 0.1536 | -0.193 | 0.2297 | 0.400 | 1.0306 |
| 808U | -1.465 | 0.1355 | 0.345 | 0.2400 | 1.739 | 1.0758 |
| 808W | 0.958 | 0.1325 | -0.180 | 0.2409 | -0.242 | 1.0720 |
| 808Y | 3.877 | 0.1309 | -0.711 | 0.2409 | -0.700 | 1.1097 |
| 809H | -0.875 | 0.1697 | 0.341 | 0.2409 | 1.125 | 1.0624 |
| 809J | 2.544 | 0.1332 | -0.425 | 0.2402 | 0.070 | 1.0032 |
| 809P | 0.562 | 0.1608 | -0.115 | 0.2391 | -0.269 | 1.0862 |
| 809R | 3.847 | 0.1539 | -0.644 | 0.2391 | -0.178 | 1.1010 |
| 809S | 3.354 | 0.1303 | -0.582 | 0.2403 | -0.286 | 1.1114 |
| 809T | 1.645 | 0.1314 | -0.332 | 0.2408 | -0.716 | 1.0924 |
| 810R | -0.915 | 0.1435 | 0.161 | 0.2417 | -0.111 | 1.0972 |
| 811P | -1.149 | 0.2171 | 0.215 | 0.2298 | 0.546 | 0.3456 |
| 811R | 2.178 | 0.1301 | -0.405 | 0.2398 | -0.433 | 1.1083 |
| 811S | 1.748 | 0.1301 | -0.305 | 0.2397 | -0.201 | 1.1061 |
| 812P | 1.693 | 0.1302 | -0.358 | 0.2401 | -0.737 | 1.1109 |
| 813R | 1.826 | 0.2301 | -0.390 | 0.2370 | -0.984 | 0.9413 |
| 813S | 1.259 | 0.1309 | -0.244 | 0.2398 | -0.360 | 1.0868 |
| 813T | 0.669 | 0.1323 | -0.171 | 0.2375 | -0.661 | 0.9934 |
| 814P | 1.710 | 0.1308 | -0.317 | 0.2404 | -0.277 | 1.1034 |
| 814R | -1.025 | 0.1422 | 0.250 | 0.2409 | 0.207 | 1.1131 |
| 814S | 1.432 | 0.1309 | -0.261 | 0.2407 | -0.277 | 1.1093 |
| 816P | -0.877 | 0.1459 | 0.163 | 0.2426 | -0.545 | 1.0736 |
| 816R | 1.468 | 0.1336 | -0.289 | 0.2413 | -0.368 | 1.0786 |
| 817S | 1.353 | 0.1338 | 0.046 | 0.2405 | 0.796 | 1.1119 |
| 823S | 1.367 | 0.1308 | -0.335 | 0.2374 | -1.018 | 1.0548 |
| 850A | 1.513 | 0.2122 | -0.233 | 0.2392 | -0.137 | 0.3693 |
| 850B | 1.126 | 0.2166 | -0.227 | 0.2455 | -1.092 | 0.4458 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 850C | 0.331 | 0.2035 | 0.022 | 0.2315 | 1.259 | 0.4112 |
| 851A | 1.362 | 0.1757 | -0.237 | 0.2409 | -0.131 | 1.1085 |
| 851C | 1.470 | 0.2114 | -0.268 | 0.2420 | -0.230 | 1.1108 |
| 851D | 2.474 | 0.1757 | -0.447 | 0.2409 | -0.408 | 1.1084 |
| 851F | 1.933 | 0.1757 | -0.357 | 0.2410 | -0.387 | 1.1097 |
| 851J | 0.681 | 0.1756 | -0.091 | 0.2407 | 0.213 | 1.1058 |
| 851K | 3.485 | 0.1758 | -0.634 | 0.2411 | -0.601 | 1.1095 |
| 851N | 3.391 | 0.1757 | -0.609 | 0.2410 | -0.521 | 1.1096 |
| 851R | 1.276 | 0.1758 | -0.227 | 0.2413 | -0.154 | 1.1120 |
| 851X | 1.792 | 0.1757 | -0.342 | 0.2409 | -0.468 | 1.1084 |
| 852X | -0.827 | 0.2927 | 0.147 | 0.1850 | -0.032 | 0.4721 |
| 856D | 2.332 | 0.1619 | -0.380 | 0.2444 | 0.115 | 1.0489 |
| 856F | 2.794 | 0.1367 | -0.442 | 0.2401 | 0.185 | 0.9592 |
| 856G | 1.672 | 0.1359 | -0.165 | 0.2381 | 0.606 | 0.9628 |
| 856J | 0.823 | 0.2102 | -0.008 | 0.1957 | 1.447 | 0.2893 |
| 856K | 2.940 | 0.1414 | -0.468 | 0.2431 | -0.255 | 1.1098 |
| 856M | 1.486 | 0.1397 | -0.369 | 0.2314 | -0.897 | 0.9987 |
| 856N | 1.010 | 0.1493 | -0.085 | 0.2439 | -0.061 | 1.1135 |
| 856O | 1.543 | 0.1441 | -0.220 | 0.2367 | -0.161 | 1.0096 |
| 856R | 2.924 | 0.1464 | -0.169 | 0.2320 | 1.116 | 1.0288 |
| 856X | 0.942 | 0.1422 | 0.025 | 0.2341 | -0.142 | 1.0864 |
| 862B | -0.512 | 0.2165 | 0.087 | 0.2459 | 0.030 | 1.1142 |
| 862O | 2.619 | 0.1405 | -0.502 | 0.2402 | -0.481 | 1.1125 |
| 877O | 3.118 | 0.1320 | -0.568 | 0.2406 | -0.654 | 1.0769 |
| 901A | 2.570 | 0.1310 | -0.506 | 0.2406 | -0.581 | 1.1098 |
| 901B | 2.438 | 0.1314 | -0.416 | 0.2394 | -0.137 | 1.0842 |
| 901C | 2.748 | 0.1313 | -0.513 | 0.2406 | -0.671 | 1.0922 |
| 901D | 3.182 | 0.1314 | -0.574 | 0.2411 | -0.508 | 1.1074 |
| 901E | 3.765 | 0.1312 | -0.652 | 0.2403 | -0.347 | 1.0966 |
| 901O | 3.688 | 0.1322 | -0.646 | 0.2415 | -0.406 | 1.1016 |
| 902O | 4.108 | 0.1300 | -0.735 | 0.2399 | -0.650 | 1.1125 |
| 903A | 2.871 | 0.1304 | -0.523 | 0.2404 | -0.402 | 1.1122 |
| 903B | 1.937 | 0.1309 | -0.323 | 0.2397 | -0.054 | 1.0930 |
| 903C | 3.251 | 0.1299 | -0.592 | 0.2398 | -0.502 | 1.1120 |
| 903O | 3.786 | 0.1301 | -0.688 | 0.2401 | -0.642 | 1.1120 |
| 904A | 2.362 | 0.1312 | -0.437 | 0.2411 | -0.388 | 1.1128 |
| 904B | 2.217 | 0.1310 | -0.420 | 0.2404 | -0.499 | 1.1029 |
| 904C | 2.572 | 0.1306 | -0.428 | 0.2396 | 0.212 | 1.0766 |
| 904D | 0.893 | 0.1319 | -0.184 | 0.2418 | 0.141 | 1.1097 |
| 904O | 3.256 | 0.1309 | -0.580 | 0.2406 | -0.406 | 1.1065 |
| 905A | 3.785 | 0.1306 | -0.679 | 0.2402 | -0.571 | 1.1080 |
| 905B | 2.063 | 0.1305 | -0.378 | 0.2405 | -0.382 | 1.1120 |
| 905C | 2.476 | 0.1308 | -0.459 | 0.2403 | -0.547 | 1.1000 |
| 905D | 2.563 | 0.1304 | -0.467 | 0.2404 | -0.420 | 1.1127 |
| 905E | 2.649 | 0.1304 | -0.478 | 0.2403 | -0.446 | 1.1124 |
| 905O | 3.895 | 0.1308 | -0.700 | 0.2408 | -0.586 | 1.1124 |
| 906A | 2.815 | 0.1306 | -0.410 | 0.2371 | 0.765 | 1.0086 |
| 906B | 2.872 | 0.1323 | -0.661 | 0.2364 | -1.597 | 0.9962 |
| 906C | 2.571 | 0.1311 | -0.434 | 0.2400 | -0.021 | 1.1040 |
| 906O | 4.066 | 0.1305 | -0.741 | 0.2404 | -0.677 | 1.1118 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 907A | 2.388 | 0.1308 | -0.393 | 0.2405 | -0.082 | 1.1070 |
| 907B | 1.554 | 0.1306 | -0.287 | 0.2405 | -0.254 | 1.1107 |
| 907O | 2.157 | 0.1312 | -0.420 | 0.2410 | -0.322 | 1.1125 |
| 908A | 3.984 | 0.1308 | -0.711 | 0.2407 | -0.565 | 1.1042 |
| 908B | 3.460 | 0.1303 | -0.623 | 0.2403 | -0.543 | 1.1125 |
| 908C | 2.969 | 0.1308 | -0.531 | 0.2398 | -0.419 | 1.0888 |
| 908D | 2.387 | 0.1316 | -0.461 | 0.2394 | -0.737 | 1.0464 |
| 908E | 3.440 | 0.1303 | -0.620 | 0.2402 | -0.553 | 1.1126 |
| 908F | 3.577 | 0.1308 | -0.642 | 0.2407 | -0.575 | 1.1122 |
| 908O | 4.892 | 0.1300 | -0.887 | 0.2399 | -0.813 | 1.1123 |
| 909A | 3.497 | 0.1311 | -0.617 | 0.2409 | -0.379 | 1.1016 |
| 909B | 1.280 | 0.1303 | -0.303 | 0.2397 | -0.756 | 1.1059 |
| 909C | 2.526 | 0.1301 | -0.447 | 0.2398 | -0.325 | 1.1084 |
| 909D | 0.827 | 0.1332 | -0.202 | 0.2396 | -0.174 | 1.1116 |
| 909E | 1.829 | 0.1300 | -0.327 | 0.2400 | -0.223 | 1.1114 |
| 909O | 3.455 | 0.1301 | -0.626 | 0.2401 | -0.564 | 1.1125 |
| 910A | 3.870 | 0.1303 | -0.700 | 0.2403 | -0.623 | 1.1121 |
| 910B | 2.389 | 0.1306 | -0.447 | 0.2405 | -0.415 | 1.1127 |
| 910C | 2.995 | 0.1304 | -0.554 | 0.2402 | -0.499 | 1.1126 |
| 910O | 3.504 | 0.1309 | -0.631 | 0.2409 | -0.592 | 1.1115 |
| 911A | 2.761 | 0.1302 | -0.493 | 0.2392 | -0.354 | 1.0880 |
| 911B | 1.679 | 0.1303 | -0.294 | 0.2401 | -0.165 | 1.1072 |
| 911C | 1.958 | 0.1303 | -0.305 | 0.2380 | 0.104 | 1.0710 |
| 911O | 3.617 | 0.1305 | -0.653 | 0.2405 | -0.589 | 1.1126 |
| 912A | 2.690 | 0.1301 | -0.465 | 0.2384 | -0.129 | 1.0656 |
| 912O | 2.799 | 0.1302 | -0.508 | 0.2399 | -0.484 | 1.1049 |
| 913A | 1.882 | 0.1304 | -0.343 | 0.2403 | -0.067 | 1.1095 |
| 913B | 1.484 | 0.1303 | -0.280 | 0.2401 | -0.263 | 1.1124 |
| 913O | 3.940 | 0.1303 | -0.711 | 0.2402 | -0.645 | 1.1124 |
| 914O | 3.170 | 0.1299 | -0.553 | 0.2394 | -0.380 | 1.1077 |
| 914P | 4.456 | 0.1299 | -0.805 | 0.2399 | -0.724 | 1.1124 |
| 914Q | 2.152 | 0.1299 | -0.389 | 0.2395 | -0.377 | 1.1092 |
| 915O | 2.641 | 0.1302 | -0.478 | 0.2399 | -0.510 | 1.1085 |
| 916O | 3.079 | 0.1313 | -0.535 | 0.2408 | -0.425 | 1.1115 |
| 917A | 3.394 | 0.1307 | -0.580 | 0.2396 | -0.250 | 1.0931 |
| 917O | 1.325 | 0.1307 | -0.195 | 0.2400 | -0.036 | 1.1112 |
| 918O | 2.596 | 0.1301 | -0.464 | 0.2399 | -0.353 | 1.1084 |
| 919O | 3.422 | 0.1343 | -0.623 | 0.2416 | -0.582 | 1.0783 |
| 921O | 2.570 | 0.1311 | -0.465 | 0.2409 | -0.405 | 1.1076 |
| 922O | 0.211 | 0.1304 | -0.083 | 0.2399 | -0.411 | 1.1047 |
| 923O | 3.999 | 0.1297 | -0.723 | 0.2395 | -0.649 | 1.1123 |
| 930A | 3.102 | 0.1303 | -0.524 | 0.2377 | -0.113 | 1.0387 |
| 930O | 2.603 | 0.1302 | -0.466 | 0.2391 | -0.398 | 1.1112 |
| 959W | -0.436 | 0.1435 | 0.104 | 0.2400 | 0.373 | 1.0393 |
| 980A | 2.211 | 0.1440 | -0.882 | 0.2360 | -6.120 | 0.6869 |
| 980C | 0.947 | 0.1450 | -0.740 | 0.2398 | -6.724 | 0.8424 |
| 980D | 0.968 | 0.1412 | -0.337 | 0.2411 | -1.900 | 0.9661 |
| 980E | 2.851 | 0.1453 | -0.804 | 0.2407 | -4.024 | 0.8458 |
| 980F | 2.600 | 0.1443 | -0.852 | 0.2387 | -4.757 | 0.8395 |
| 980H | 2.001 | 0.1456 | -0.759 | 0.2375 | -5.456 | 0.6419 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 980T | 0.362 | 0.1476 | 0.093 | 0.2377 | 1.788 | 0.7094 |
| 980U | 0.956 | 0.1499 | -0.279 | 0.2409 | -1.525 | 0.7515 |
| 980X | 2.034 | 0.1429 | -0.386 | 0.2376 | -0.615 | 0.7764 |
| 981X | 1.904 | 0.1400 | -0.312 | 0.2345 | -0.143 | 0.7823 |
| 996O | 1.931 | 0.1601 | -0.350 | 0.2401 | -0.313 | 1.1124 |
| 997O | 1.677 | 0.1342 | -0.304 | 0.2434 | -0.315 | 1.1136 |

## 9.3 R code for data

```
library(tidyverse)
# Set WD
setwd("C:/Users/sigur/OneDrive/Dokumenter/Helsedata")
getwd()
rm(list=ls())

# Import data
library(readxl)
data1 <- read_excel("Aggregerte-sykehusopphold.xlsx")
data2 <- read_excel("KPP-2017-2019.xlsx", sheet = 1)
data3 <- read_excel("KPP-2017-2019.xlsx", sheet = 2)
data4 <- read_excel("KPP-2020-2021.xlsx")
NordDRG_2019_compl <- read_excel("NordDRG 2019 compl.xlsx")
CC_Egenskaper <- read_excel("DRG_Masterliste_2017_Somatikk.xlsx",
                        sheet = "CC_Egenskaper")
DRG_Masterliste_2017_Somatikk <- read_excel("DRG_Masterliste_2017_Somatikk.xlsx",
                                    sheet = "Masterliste")
vekt2017 <- DRG_Masterliste_2017_Somatikk[,c(1,6)]
vekt2017$Year <- 2017
colnames(vekt2017)[1] = "DRG"
colnames(vekt2017)[2] = "DRGWeight"
vekt2017$DRG <- as.factor(vekt2017$DRG)

######################
### Admissions data #
######################

# Gender as factor, 1 = Female and 2 = Male
data1 %>%
  group_by(DRG) %>%
  mutate(Sex=as.numeric(as.factor(Gender))) -> data1

# Column bind female data to male data rows
Fdata1 <- subset(data1, Sex==1)
data1 <- subset(data1, Sex==2)
data1 <- full_join(data1,Fdata1, by = c("DRG","HF","Year"))
```

```
# Replacing NA with 0
data1$Admissions.x[is.na(data1$Admissions.x)] <- 0
data1$Admissions.y[is.na(data1$Admissions.y)] <- 0
data1$Age.x[is.na(data1$Age.x)] <- 0
data1$Age.y[is.na(data1$Age.y)] <- 0
data1$Sum_stay_DRGpoints.x[is.na(data1$Sum_stay_DRGpoints.x)] <- 0
data1$Sum_stay_DRGpoints.y[is.na(data1$Sum_stay_DRGpoints.y)] <- 0
data1$LOS.x[is.na(data1$LOS.x)] <- 0
data1$LOS.y[is.na(data1$LOS.y)] <- 0

# making factors
data1$HF <- as.factor(data1$HF)
data1$DRG <- as.factor(data1$DRG)
data1$RHF <- as.factor(data1$RHF.x)

# Calculate combined admissions, DRG-point value, gender neutral age avg and % female admissions
data1 %>%
  mutate(
    Admissions = Admissions.x+Admissions.y,
    Sum_stay_DRG = Sum_stay_DRGpoints.x+Sum_stay_DRGpoints.y,
    DRGWeight = Sum_stay_DRG/Admissions,
    LOS = (LOS.x*Admissions.x+LOS.y*Admissions.y)/Admissions,
    LOSxDRGW = LOS*DRGWeight,
    #dDRGWeight = DRGWeight-lag(DRGWeight),
    Age = (Age.x*Admissions.x+Age.y*Admissions.y)/Admissions,
    Femalepct = Admissions.y/(Admissions.x+Admissions.y)
    ) -> data1

# Selecting variables for analysis and tidying
data1 %>%
  select(
    Year, HF, RHF, DRG, DRG_Name.x, Type_DRG.x, Admissions,
    Sum_stay_DRG, DRGWeight, LOS, LOSxDRGW, Age, Femalepct
    ) -> df
rm("data1", "Fdata1")

################
### Cost data #
################

# Selecting variables, combining and tidying
data4 <- data4[c(-(3:13),-15,-17)]
data4 <- data4[, c(4, 3, 1, 2, 5)]

costdata <- rbind(data2,data3,data4)
costdata$HF <- as.factor(costdata$HF)
costdata$DRG <- as.factor(costdata$DRG)
df <- full_join(df, costdata, by = c("DRG","HF","Year"))
rm("data2", "data3", "data4", "costdata")
```

```
# Omit observations without either price or cost data and n < 5
# for compliance to request from data provider
df <- df[complete.cases(df[ , c('Admissions.x', 'Sum_stay_DRG', 'Admissions.y', 'Sum')]), ]
df <- df[df$Admissions.x > 4,]
which(df$Admissions < 5)
# Admissions data does not match between the two data sources.
# Data1 is compiled by RHF and data2:4 is compiled by HF,
# causing prices and costs to be be based on a different number of patients.
# continue with the admission numbers provided by Helse Nord and adjust
# hospital costs.

# Adjusting cost numbers to price-linked quantities
df %>%
  mutate(
    Sum = Sum/Admissions.y*Admissions.x
    ) -> df
names(df)[names(df) == "Admissions.x"] <- "Admissions"
df <- df[-14]
which(is.na(df))

# Sorting and checking for equal HF factors between datasets manually.
# leaving dates as number format
attach(df)
df <- df[order(Year, HF, DRG),]
detach(df)

# Converting costs to DRG-points and calculating dDRGWeight by dividing
# Sum by the yearly avg patient cost (DRGWeight = 1) from Helsedirektoratet.
df2018 <- df %>%
  subset(Year == 2018) %>%
  mutate(
    DRGCost = Sum/43428/Admissions,
    DRGProfit = DRGWeight-DRGCost,
    TotProfit = DRGProfit*Admissions) # Unit price = 43 428
df2019 <- df %>%
  subset(Year == 2019) %>%
  mutate(
    DRGCost = Sum/44654/Admissions,
    DRGProfit = DRGWeight-DRGCost,
    TotProfit = DRGProfit*Admissions) # Unit price = 44 654
df2020 <- df %>%
  subset(Year == 2020) %>%
  mutate(
    DRGCost = Sum/45808/Admissions,
    DRGProfit = DRGWeight-DRGCost,
    TotProfit = DRGProfit*Admissions) # Unit price = 45 808
df2021 <- df %>%
  subset(Year == 2021) %>%
  mutate(
    DRGCost = Sum/46719/Admissions,
    DRGProfit = DRGWeight-DRGCost,
    TotProfit = DRGProfit*Admissions) # Unit price = 46 719
```

```
df <- rbind(df2018, df2019, df2020, df2021)
rm("df2018", "df2019", "df2020", "df2021")

# Making a more balanced panel
length(levels(df$HF))  # 25 Hospitals in unbalanced panel
length(levels(df$DRG)) # 901 DRGs in unbalanced panel
length(df$DRG)         # 49123 Observations in unbalanced panel
df <- df %>%
  group_by(HF, DRG) %>%
  tally() %>%
  full_join(df)
df <- subset(df, n==4)

# Easiest way to check if some factors are unused
df$HF <- as.factor(as.character(df$HF))
df$DRG <- as.factor(as.character(df$DRG))
df$RHF <- as.factor(as.character(df$RHF))

# Only change in observations
length(levels(df$HF))  # 20 Hospitals in unbalanced panel
length(levels(df$DRG)) # 678 DRGs in balanced panel
length(df$DRG)         # 38520 Observations in unbalanced panel

# Making yearly change in profit variable
df <- df %>%
  group_by(HF, DRG) %>%
  mutate(dDRGW = DRGWeight-lag(DRGWeight),
         dDRGP = DRGProfit-lag(DRGProfit),
         dDRGC = DRGCost-lag(DRGCost),
         SumDRGP = Admissions*DRGProfit)
df$dDRGW[is.na(df$dDRGW)] <- 0
df$dDRGP[is.na(df$dDRGP)] <- 0
df$dDRGC[is.na(df$dDRGC)] <- 0

# quick fix to implement dDRGW values for 2018
df <- full_join(df,vekt2017[1:2], by = c("DRG"))
df2018 <- df %>% subset(Year == 2018) %>% mutate(dDRGW = DRGWeight.x-DRGWeight.y)
dfother <- df %>% subset(Year > 2018)
df <- rbind(df2018,dfother)
df <- subset(df, select = -DRGWeight.y)

## Make time Dummy
df <- cbind(df, as.data.frame(model.matrix( ~ as.factor(Year) - 1, assign=c(0,1,1,1), data=df )))
which(is.na(df$Admissions))
df <- df %>% subset(HF != "Diakonhjemmet Sykehus")
df <- df %>% subset(HF != "Haraldsplass Diakonale sykehus")

# Tidying
names(df) <- c("HF", "DRG", "n", "Year", "RHF", "DRG_Name", "Type_DRG",
               "Admissions", "SumDRGW", "DRGW", "LOS", "LOSxDRGW",
               "Age", "Fpct", "SumDRGC", "DRGC", "DRGP", "TDRGP", "dDRGW",
               "dDRGP", "dDRGC", "SumDRGP", "Y2018", "Y2019", "Y2020", "Y2021" )
```

```
col_order <- c("Year", "RHF", "HF", "DRG", "n", "DRG_Name", "Type_DRG",
           "Admissions","Age", "Fpct", "LOS", "LOSxDRGW", "SumDRGW", "SumDRGC", "SumDRGP",
           "DRGW", "DRGC", "DRGP", "dDRGW", "dDRGC", "dDRGP",
           "Y2018", "Y2019", "Y2020", "Y2021" )
df <- df[, col_order]

na_rows <- df[is.na(df$dDRGW), ]
na_rows$DRG <- as.factor(as.character(na_rows$DRG))
levels(na_rows$DRG)
df <- anti_join(df, na_rows, by = "DRG")
df2 <- df[,-5]
df <- df %>%
  group_by(HF, DRG) %>%
  tally() %>%
  full_join(df)
df <- subset(df, n==4)

# Hide HF
df$HF <- as.factor(as.numeric(as.factor(as.character(df$HF))))
levels(df$HF)


####################
### Saving file ###
####################
### write xlsx
library(writexl)
attach(df)
exceldf <- df[order(HF, DRG, Year),]
detach(df)
write_xlsx(exceldf, "C:/Users/sigur/OneDrive/Dokumenter/Helsedata/data.xlsx")

# More changes and save again
rm(list=ls())
full.df <- read_excel("data.xlsx")

colnames(full.df)[3]  <- "#ofYears"
# Filter away DRGs with weight of 0 and less than two hospitals do treatment
full.df <- full.df %>% filter(DRGW>0)
full.df <- full.df %>% group_by(DRG) %>% tally() %>% full_join(full.df)
full.df <- full.df %>% filter(n>8)
# Remove rehabilitation 462A and 462B
full.df <- full.df %>% filter(DRG != "462A" & DRG != "462B")
# Add subject indicators and ln(Admissions)
subject <- rep(1:8839,each=4)
full.df <- cbind(full.df, subject)
full.df <- full.df %>% mutate(lnAdm=log(Admissions))
full.df$LOS <- full.df$LOS/full.df$Admissions

write_xlsx(full.df, "C:/Users/sigur/OneDrive/Dokumenter/Helsedata/data.xlsx")
```

## 9.4 R code for model and testing

```
library(tidyverse) # ggplot, dplyr etc
library(plm) # panel data models
library(lme4) # mixed effect models
library(flexplot) # model comparison and visualization for mlm
library(modelsummary) # Summary
library(lmtest)
library(moments)
library(gridExtra)
library(multilevelTools)

setwd("C:/Users/sigur/OneDrive/Dokumenter/Helsedata")
getwd()
rm(list=ls())
#load(".RData")

#Load prepared data
library(readxl)
full.df <- read_excel("data.xlsx")

# Fixing factors
full.df$Year <- as.factor(full.df$Year)
full.df$HF <- as.factor(full.df$HF)
full.df$DRG <- as.factor(full.df$DRG)
full.df$RHF <- as.factor(full.df$RHF)

# select data for use, variables for patient characteristics were unused
df <- full.df %>% subset(select=c("subject", "HF", "Year", "DRG", "Admissions", "lnAdm", "DRGP",
"DRGW",
                                  "dDRGW", "Age", "Fpct", "LOS", "LOSxDRGW"))
df <- arrange(df, HF, DRG)
pdf <- pdata.frame(df, index = c("subject", "Year"))

# Grouping variables
df %>% group_by(HF) %>% tally() # DRGs in each hospital, /4
df %>% group_by(DRG) %>% tally() %>% print()

# Looking at extreme values
full.df[1:22] %>% filter(DRGP > 5)
full.df[1:22] %>% filter(DRGW > 20)
full.df[1:22] %>% filter(DRGP < (-10))
full.df[1:22] %>% filter(DRGP > 10)
full.df[1:22] %>% filter(dDRGW > 3)
full.df[1:22] %>% filter(dDRGW < (-3))
full.df[1:22] %>% filter(DRGW < 0.01)
```

```
# Cox-box test of Admissions
hist(df$Admissions)
admission <- df$Admissions
boxcox(lm(admission ~ 1)) # Visual examination gives lambda close to 0, indicates log transformation is suitable for the data

# Skewness and kurt
library(moments)
skewness(new) # skewed right of mean, result 0,59
kurtosis(new) # below the threshold of excess kurtosis, result 2,6 (<3)
skewness(df$DRGP) # skewed -9.314194
kurtosis(df$DRGP) # 265.0091
####################################
######## 1st level models #########
####################################

# 1 level models
# Simple model
pooled1 <- lm(lnAdm ~ DRGP, data=df)
summary(pooled1)

# Controlling for HF, DRG and Year
# Like model 1 in Januleviciute et. al.
pooled2 <- lm(lnAdm ~ HF + DRG + Year + DRGP, data=pdf)
summary(pooled2)
# DRGP: estimate 0.0188968,
#       Std. er  0.0036522,
#       t-value  5.174,
#       p-value  2.30e-07

# Like model 1 in Januleviciute et. al. with price and change in price
pooled3 <- lm(lnAdm ~ HF + DRG + Year + DRGP + DRGW + dDRGW, data=pdf)
summary(pooled3)
# DRGP: estimate 0.019330,
#       Std. er  0.003683,
#       t-value  5.174,
#       p-value  2.30e-07

# Like model 2 in Januleviciute et. al.
pooled4 <- lm(lnAdm ~ HF + DRG + Year + DRG*Year + DRGP, data=pdf)
summary <- summary(pooled3)[["coefficients"]]
# DRGP: estimate 0.01901994,
#       Std. er  0.003826312,
#       t-value  4.970828,
#       p-value  6.700232e-07

# PLM
fixed  <- plm(lnAdm ~ HF + DRG + Year + DRGP, data=pdf, model = "within")
random <- plm(lnAdm ~ HF + DRG + Year + DRGP, data=pdf, model = "random")
random2 <- plm(lnAdm ~ HF + DRG + Year + DRGP + DRGW + dDRGW, data=pdf, model = "random")
summary(fixed) # DRGP      0.0137762,  0.0027471,  5.0149, 5.341e-07 ***
summary(random) # DRGP        0.01453093  0.00262273   5.5404 3.018e-08 ***
```

```
summary(random2) # DRGP        0.0153773  0.0026732   5.7523 8.803e-09 ***
# Hausman test
phtest(fixed, random) # Random effect wins, p = 0.9312
phtest(fixed, random2) # Random effect wins, p = 0.4649


##################################
### Multi-level model in lme4 ###
##################################

# Base model for HF/DRG nested structure
base.HF.HFDRG <- lmer(lnAdm ~ 1 + (1 | HF) + (1 | HF:DRG), data=df)
performance::icc(base.HF.HFDRG, by_group = TRUE) # HF:DRG 0.947, HF 0.033

# Base model for HF/DRG nested structure with crossed DRG
base.DRG.HF.HFDRG <- lmer(lnAdm ~ 1 + (1 | DRG) + (1 | HF) + (1 | HF:DRG), data=df)
summary(base.DRG.HF.HFDRG)
performance::icc(base.DRG.HF.HFDRG, by_group = TRUE) # Group ICC, HF:DRG  0.064, DRG 0.821, HF
0.097

### Testing crossed structure and simple nested structure
anova(base.HF.HFDRG, base.DRG.HF.HFDRG) # Nested and crossed structure wins, it represents the
variation in the model bettwe

# Testing from maximal to converging reduced
maximal <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG) + (1 +
DRGP | HF) + (1 + DRGP | HF:DRG), data = df)
summary(maximal)
estimates(maximal)
### Step 1, Number of dimensions supported
maximal.PCA<-rePCA(maximal)
summary(maximal.PCA) # HF 2, DRG 3, HF:DRG 2, though n-1 components has above 0.99%
### Step 2, Model is within number of supported parameters

### Step 3, Forcing 0 correlation
maximal <- readRDS(file = "maximal.rds")
maximal.noCor1 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG)
+ (1 + DRGP | HF) + (1 + DRGP || HF:DRG), data = df)
summary(maximal.noCor1)
lrtest(maximal, maximal.noCor1) # Maximal model wins, but only 4%

maximal.noCor2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG)
+ (1 + DRGP || HF) + (1 + DRGP || HF:DRG), data = df)
summary(maximal.noCor2) # Converged
lrtest(maximal, maximal.noCor2) # Maximal model wins, but only 4%
lrtest(maximal.noCor1, maximal.noCor2) # Maximal.noCor1


maximal.noCor2.1 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW |
DRG) + (1 + DRGP || HF) + (1 + DRGP | HF:DRG), data = df)
summary(maximal.noCor2.1) # Converged
lrtest(maximal, maximal.noCor2.1) # Maximal model wins, but only 2%
```

```
lrtest(maximal.noCor2, maximal.noCor2.1) # Equal, 25%

maximal.noCor4 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW || DRG)
+ (1 + DRGP | HF) + (1 + DRGP | HF:DRG), data = df)
summary(maximal.noCor4) # Did not converge
lrtest(maximal, maximal.noCor4) # Maximal model wins! p < 2.2e-16 ***

maximal.noCor4.1 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW ||
DRG) + (1 + DRGP | HF) + (1 + DRGP || HF:DRG), data = df)
summary(maximal.noCor4.1) # Converged
lrtest(maximal, maximal.noCor4.1) # Maximal model wins! p < 2.2e-16 ***

maximal.noCor4.2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW ||
DRG) + (1 + DRGP || HF) + (1 + DRGP | HF:DRG), data = df)
summary(maximal.noCor4.2) # Converged
lrtest(maximal, maximal.noCor4.2) # Maximal model wins! p < 2.2e-16 ***
lrtest(maximal.noCor4.1, maximal.noCor4.2) # noCor4.1 wins! p < 2.2e-16 ***
                        # However the models are not nested, but overlapping.
                        # unsure about this high p with low LRT diff Vuong (1989) LRT model
selection

maximal.noCor3 <- readRDS(file = "maximal.noCor3.rds")
maximal.noCor3 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW || DRG)
+ (1 + DRGP || HF) + (1 + DRGP || HF:DRG), data = df)
summary(maximal.noCor3) # converged
maximal.noCor3.PCA<-rePCA(maximal.noCor3)
summary(maximal.noCor3.PCA)
lrtest(maximal, maximal.noCor3) # Maximal model wins! p < 2.2e-16 ***

# For markdown
comp1 <- model.comparison(maximal, maximal.noCor2.1)
comp2 <- model.comparison(maximal, maximal.noCor1)
comp3 <- model.comparison(maximal, maximal.noCor2)
comp4 <- model.comparison(maximal, maximal.noCor4)
comp5 <- model.comparison(maximal, maximal.noCor4.2)
comp6 <- model.comparison(maximal, maximal.noCor4.1)
comp7 <- model.comparison(maximal, maximal.noCor3)

######################
### Extra testing ###
######################

# Split DRG group
# DRGW with intercept
#maximal.noCor4.3 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW | DRG) + (0 +
dDRGW | DRG) + (1 + DRGP | HF) + (1 + DRGP | HF:DRG), data = df)
#summary(maximal.noCor4.3) # Converged less than noCor1
#maximal.noCor4.3.1 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW | DRG) + (0 +
dDRGW | DRG) + (1 + DRGP | HF) + (1 + DRGP || HF:DRG), data = df)
#summary(maximal.noCor4.3.1) # Does not converge
#maximal.noCor4.3.2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW | DRG) + (0 +
dDRGW | DRG) + (1 + DRGP || HF) + (1 + DRGP | HF:DRG), data = df)
```

```
#summary(maximal.noCor4.3.2) # Converges
#maximal.noCor4.3.3 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW | DRG) + (0 + dDRGW | DRG) + (1 + DRGP || HF) + (1 + DRGP || HF:DRG), data = df)
#summary(maximal.noCor4.3.3) # Converges
#lrtest(maximal, maximal.noCor4.3.2) # Maximal model wins, however a much smaller p than others, p = 0.00158
#lrtest(maximal, maximal.noCor4.3.3) # Maximal model wins, however a much smaller p than others, p = 0.00227
#lrtest(maximal.noCor4.3.2, maximal.noCor4.3.3) # Not significantly different, favouring 4.3.3 for complexity penalty

# This for inclusion dDRGW correlation
#lrtest(maximal.noCor2, maximal.noCor4.3.3)

# dDRGW with intercept, not favourite
#maximal.noCor4.4 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + dDRGW | DRG) + (0 + DRGW | DRG) + (1 + DRGP | HF) + (1 + DRGP | HF:DRG), data = df)
#summary(maximal.noCor4.4) # Converged
#lrtest(maximal, maximal.noCor4.4) # Maximal model wins! p < 2.2e-16 ***
#maximal.noCor4.4.1 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + dDRGW | DRG) + (0 + DRGW | DRG) + (1 + DRGP | HF) + (1 + DRGP || HF:DRG), data = df)
#summary(maximal.noCor4.4.1) # Converged
#lrtest(maximal, maximal.noCor4.4.1) # Maximal model wins! p < 2.2e-16 ***
#maximal.noCor4.4.2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + dDRGW | DRG) + (0 + DRGW | DRG) + (1 + DRGP || HF) + (1 + DRGP | HF:DRG), data = df)
#summary(maximal.noCor4.4.2) # Converges
#lrtest(maximal, maximal.noCor4.4.2) # Maximal model wins! p < 2.2e-16 ***
#maximal.noCor4.4.3 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + dDRGW | DRG) + (0 + DRGW | DRG) + (1 + DRGP || HF) + (1 + DRGP || HF:DRG), data = df)
#summary(maximal.noCor4.4.3) # Converges
#lrtest(maximal, maximal.noCor4.4.2) # Maximal model wins! p < 2.2e-16 ***

#lrtest(maximal.noCor4.4, maximal.noCor4.4.1) # Not significantly different
#lrtest(maximal.noCor4.4, maximal.noCor4.4.2) # Sign diff 2%
#lrtest(maximal.noCor4.4, maximal.noCor4.4.3) # Sign diff 4.4%
#lrtest(maximal.noCor4.3.3, maximal.noCor3) # Significant difference, 4.3.3 wins!

### Step 4 Removing variance components from maximal model and
### Step 5 Adding correlations
# Estimating model without dDRGP, but with correlations
#submaximal <- readRDS(file = "submaximal.rds")
#submaximal <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + (1 + DRGW | DRG) + (1 + DRGP | HF) + (1 + DRGP | HF:DRG), data = df)
#summary(submaximal) # Converges with all correlations
#submaximal.PCA<-rePCA(submaximal)
#summary(submaximal.PCA)
#lrtest(maximal, submaximal) # Maximal model wins! p < 2.2e-16 ***
# Removing HF:DRG specific intercept
#sub2maximal <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG) + (1 + DRGP | HF) + (0 + DRGP | HF:DRG), data = df)
#summary(sub2maximal) # Singular, supported dimensions in HF reduced to 1
#lrtest(maximal, sub2maximal) # Maximal model wins, DRG intercept significant
```

```
# Removing DRG specific intercept
#sub3maximal <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (0 + DRGW + dDRGW | DRG) +
(1 + DRGP | HF) + (1 + DRGP | HF:DRG), data = df)
#summary(sub3maximal)
#lrtest(maximal, sub3maximal) # Maximal model wins, DRG intercept significant
# Removing correlations
#sub3maximal.1 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (0 + DRGW + dDRGW | DRG)
+ (1 + DRGP | HF) + (1 + DRGP || HF:DRG), data = df)
#sub3maximal.2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (0 + DRGW + dDRGW | DRG)
+ (1 + DRGP || HF) + (1 + DRGP || HF:DRG), data = df)
#summary(sub3maximal.2)
#lrtest(maximal, sub3maximal.2) # Maximal no correlation model wins! p < 2.2e-16 ***
# Removing HF specific intercept
#sub4maximal <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG) +
(0 + DRGP | HF) + (1 + DRGP | HF:DRG), data = df)
#sub4maximal.2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG)
+ (0 + DRGP || HF) + (1 + DRGP || HF:DRG), data = df)

#summary(sub4maximal) # Does not converge
#lrtest(maximal, sub4maximal.2) # Maximal model wins, HF intercept significant
# Removing HF:DRG DRGP
#sub5maximal <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG) +
(1 + DRGP | HF) + (1 | HF:DRG), data = df)
#sub5maximal.2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG)
+ (1 + DRGP || HF) + (1 | HF:DRG), data = df)
#lrtest(maximal, sub5maximal.2) # Maximal no correlation model wins!
#summary(sub5maximal) # Does not converge
# Removing HF DRGP
#sub6maximal <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW + dDRGW | DRG) +
(1 | HF) + (1 + DRGP | HF:DRG), data = df)
#summary(sub6maximal) # Does not converge
# Removing DRG DRGW
#sub7maximal <- lmer(lnAdm ~ 1 + Year + DRGP + dDRGW + (1 + dDRGW | DRG) + (1 | HF) + (1 +
DRGP | HF:DRG), data = df)
#sub7maximal.2 <- lmer(lnAdm ~ 1 + Year + DRGP + dDRGW + (1 + dDRGW | DRG) + (1 + DRGP || HF)
+ (1 | HF:DRG), data = df)
#summary(sub7maximal) # Does not converge

### Step 4 and 5  for the selected reduce correlation model
# Reduced number of steps
#summary(maximal.noCor4.4.3) # reduced correlation winner
# Drop dDRGW
#reduced.noCor.win.nodDRGW <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + (1 + DRGW | DRG) + (1 +
DRGP || HF) + (1 + DRGP || HF:DRG), data = df)
#summary(reduced.noCor.win.nodDRGW)
#lrtest(maximal.noCor2, reduced.noCor.win.nodDRGW) # dDRGW is significant
# reintroduce correlation
#reduced.noCor.win.nodDRGW.moreCor1 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + (1 + DRGW |
DRG) + (1 + DRGP | HF) + (1 + DRGP || HF:DRG), data = df)
#reduced.noCor.win.nodDRGW.moreCor2 <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + (1 + DRGW |
DRG) + (1 + DRGP || HF) + (1 + DRGP | HF:DRG), data = df)
```

```
#lrtest(reduced.noCor.win.nodDRGW,reduced.noCor.win.nodDRGW.moreCor1) # HF correlation is not significantly different, 17%
#lrtest(reduced.noCor.win.nodDRGW,reduced.noCor.win.nodDRGW.moreCor2) # HF correlation is not significantly different, 17%

# Drop HF:DRG DRGP
#reduced.noCor.win.noDRGP.HFDRG <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW | DRG) + (0 + dDRGW | DRG) + (1 + DRGP || HF) + (1 | HF:DRG), data = df)
#summary(reduced.noCor.win.noDRGP.HFDRG) # Does not converge

# Drop HF:DRG Intercept
#reduced.noCor.win.noInterc.HFDRG <- lmer(lnAdm ~ 1 + Year + DRGP + DRGW + dDRGW + (1 + DRGW | DRG) + (0 + dDRGW | DRG) + (1 + DRGP || HF) + (0 + DRGP | HF:DRG), data = df)
#summary(reduced.noCor.win.noInterc.HFDRG) # Singular
#reduced.noCor.win.noInterc.HFDRG.PCA<-rePCA(reduced.noCor.win.noInterc.HFDRG)
#summary(reduced.noCor.win.noInterc.HFDRG.PCA) # dDRGW ~0 sd, HF:DRGP low df
                                # No reason to add more correlation to singular

### Step 6 Not solution, maximal model can find solution.
### Procedure failed to provide a model converging alternative without loss of goodness-of-fit

#######################################################
##### Comparing the alternatives that converged ####
#######################################################
#lrtest(maximal, maximal.noCor3) # Maximal model wins, covariance is significant
#lrtest(maximal, submaximal) # Maximal model wins, dDRGW is significant
#lrtest(maximal, maximal.noCor4.3.3) # Maximal model wins, covariance is significant, but only 2%
#lrtest(maximal.noCor4.3.3, maximal.noCor3) # Significant diff. 4.3.3 wins

# Using no maximal model without correlations because Bates et. al. (2015)
# "the primary reason for dealing with the random-effects structure is to
# obtain as powerful tests as justified of the fixed effects ...
# Therefore, it is reasonable to remove variance components/correlation parameters
# from the model if they are not supported by the data"

#fixef(maximal); fixef(maximal.noCor2) # t-values of max -2.9, noCor3 -1.2
```

```
####################################
######### Post analysis #############
####################################

# Displaying results
modsum_list <- modelsummary(maximal.noCor2,
        shape = response + term + statistic ~ model,
        coef_map = c('(Intercept)' = '(Intercept)', 'Year2019' = 'Year 2019',
                'Year2020' = 'Year 2020', 'Year2021' = 'Year 2021',
                'DRGP' = 'DRGP', 'DRGW' = 'DRGW', 'dDRGW' = 'dDRGW',
                'SD (Intercept HF)' = 'SD Intercept HF',
                'SD (Intercept DRG)' = 'SD Intercept DRG',
                'SD (Intercept HF.DRG)' = 'SD Intercept HF:DRG',
                'SD (DRGP HF)' = 'SD DRGP HF',
                'SD (DRGP HF.DRG)' = 'SD DRGP HF:DRGP',
                'SD (DRGW DRG)' = 'SD DRGW',
                'SD (dDRGW DRG)' = 'SD dDRGW',
                'SD (Observations)' = 'Residuals'),
        output = "modelsummary_list")
modsum_list <- saveRDS(modsum_list, file = "modsumlist.max.noCor.rds")


# Extracting random effects
maximal.noCor2 <- readRDS(file = "maximal.noCor2.rds") # No name change in code, but model is
noCor2
maximal.ranef <- ranef(maximal.noCor2)

maximal.ranef.df <- as.data.frame(maximal.ranef)
maximal.ranef.df <- separate(maximal.ranef.df, grp, sep = ":", fill = "left", into = c("HF", "DRG"))

# Bad low tech edit fix HF number in DRG column
maximal.ranef.df$HF[19512] <- 1;maximal.ranef.df$HF[19513] <- 10;maximal.ranef.df$HF[19514] <-
11;maximal.ranef.df$HF[19515] <- 12;
maximal.ranef.df$HF[19516] <- 13;maximal.ranef.df$HF[19517] <- 14;maximal.ranef.df$HF[19518] <-
15;maximal.ranef.df$HF[19519] <- 16;
maximal.ranef.df$HF[19520] <- 17;maximal.ranef.df$HF[19521] <- 18;maximal.ranef.df$HF[19522] <-
2;maximal.ranef.df$HF[19523] <- 3;
maximal.ranef.df$HF[19524] <- 4;maximal.ranef.df$HF[19525] <- 5;maximal.ranef.df$HF[19526] <-
6;maximal.ranef.df$HF[19527] <- 7;
maximal.ranef.df$HF[19528] <- 8;maximal.ranef.df$HF[19529] <- 9;maximal.ranef.df$HF[19530] <-
1;maximal.ranef.df$HF[19531] <- 10;
maximal.ranef.df$HF[19532] <- 11;maximal.ranef.df$HF[19533] <- 12;maximal.ranef.df$HF[19534] <-
13;maximal.ranef.df$HF[19535] <- 14;
maximal.ranef.df$HF[19536] <- 15;maximal.ranef.df$HF[19537] <- 16;maximal.ranef.df$HF[19538] <-
17;maximal.ranef.df$HF[19539] <- 18;
maximal.ranef.df$HF[19540] <- 2;maximal.ranef.df$HF[19541] <- 3;maximal.ranef.df$HF[19542] <-
4;maximal.ranef.df$HF[19543] <- 5;
maximal.ranef.df$HF[19544] <- 6;maximal.ranef.df$HF[19545] <- 7;maximal.ranef.df$HF[19546] <-
8;maximal.ranef.df$HF[19547] <- 9;

maximal.ranef.HF <- maximal.ranef.df[19512:19547,]
```

```
maximal.ranef.HF <- full_join(subset(maximal.ranef.HF, term == "(Intercept)"),
subset(maximal.ranef.HF, term == "DRGP"), by = "HF")
maximal.ranef.HF <- maximal.ranef.HF %>%
 rename("HF.Intercept.Value" = "condval.x",
       "HF.Intercept.SD" = "condsd.x",
       "HF.DRGP.Value" = "condval.y",
       "HF.DRGP.SD" = "condsd.y",) %>%
 select(HF, HF.Intercept.Value, HF.Intercept.SD, HF.DRGP.Value, HF.DRGP.SD)

maximal.ranef.DRG <- maximal.ranef.df[17679:19511,]
maximal.ranef.DRG2 <- full_join(subset(maximal.ranef.DRG, term == "(Intercept)"),
subset(maximal.ranef.DRG, term == "DRGW"), by = "DRG")
maximal.ranef.DRG <- full_join(maximal.ranef.DRG2, subset(maximal.ranef.DRG, term == "dDRGW"),
by = "DRG")
maximal.ranef.DRG <- maximal.ranef.DRG %>%
 rename("DRG.Intercept.Value" = "condval.x",
       "DRG.Intercept.SD" = "condsd.x",
       "DRG.DRGW.Value" = "condval.y",
       "DRG.DRGW.SD" = "condsd.y",
       "DRG.dDRGW.Value" = "condval",
       "DRG.dDRGW.SD" = "condsd",) %>%
 select(DRG, DRG.Intercept.Value, DRG.Intercept.SD, DRG.DRGW.Value, DRG.DRGW.SD,
DRG.dDRGW.Value, DRG.dDRGW.SD)
saveRDS(maximal.ranef.DRG, file = "maximal.ranef.DRG.rds")
maximal.ranef.HFDRG <- maximal.ranef.df[1:17678,]
maximal.ranef.HFDRG <- full_join(subset(maximal.ranef.HFDRG, term == "(Intercept)"),
subset(maximal.ranef.HFDRG, term == "DRGP"), by = c("HF", "DRG"))
maximal.ranef.HFDRG <- maximal.ranef.HFDRG %>%
 rename("HFDRG.Intercept.Value" = "condval.x",
       "HFDRG.Intercept.SD" = "condsd.x",
       "HFDRG.DRGP.Value" = "condval.y",
       "HFDRG.DRGP.SD" = "condsd.y",) %>%
 select(HF, DRG, HFDRG.Intercept.Value, HFDRG.Intercept.SD, HFDRG.DRGP.Value, HFDRG.DRGP.SD)
saveRDS(maximal.ranef.HFDRG, file = "maximal.ranef.HFDRG.rds")
maximal.ranef.sorted <- full_join(maximal.ranef.HF, maximal.ranef.HFDRG, by = "HF")
maximal.ranef.sorted <- full_join(maximal.ranef.sorted, maximal.ranef.DRG, by = "DRG")



##################
### Residuals ###
##################

### Linearity, see Fox 2008

plot(df$lnAdm,resid(maximal.noCor2)) # Maybe a pattern
plot(abs(df$lnAdmresid(maximal.noCor2, df$lnAdm))) # maybe because of the lower bounds of
residuals when close to 0
linearity <- ggplot(df, aes(resid(maximal.noCor2), lnAdm)) + # No known pattern
 geom_point(alpha = 0.3) +
 xlab("Residuals") +
 ylab("ln(Adm)") +
```

```
  labs(title = "Residual plot for assumption of linearity")

# Multicollinearity
car::vif(maximal.noCor2) # all ~1, looks good

# Homogeneity of variance (test for heteroscedasticity)
Resid.subject <- lm(abs(resid(maximal.noCor2))^2 ~ subject, data=df) # Subject is equivalent of
HF:DRG because they are each unique
anova(Resid.subject) #
# No homogeneity for any group variance

# Residual homoscedasticity
plot_redres(maximal.noCor2, type = "raw_cond")

plot(fitted(maximal.noCor2), resid(maximal.noCor2), xlab = "Fitted values", ylab = "Residuals") #
Residuals are heteroscedastic
plot(resid(maximal.noCor2))
heteroscedasticity <- ggplot(df, aes(fitted(maximal.noCor2), resid(maximal.noCor2))) + # No known
pattern
  geom_point(alpha = 0.3) +
  xlab("Fitted values") +
  ylab("Residuals") +
  labs(title = "Residual plot for heteroscedasticity")
# Normality
qq <- qqnorm(resid(maximal.noCor2))
qqline(resid(maximal.noCor2), distribution = qnorm)
histo <- hist((resid(maximal.noCor2) - mean(resid(maximal.noCor2))) / sd(resid(maximal.noCor2)),
freq = FALSE, breaks = 50, xlab = "Standardized residuals"); curve(dnorm, add = TRUE);
skewness((resid(maximal.noCor2)-mean(resid(maximal.noCor2)))/sd(resid(maximal.noCor2))) #
kurtosis((resid(maximal.noCor2)-mean(resid(maximal.noCor2)))/sd(resid(maximal.noCor2))) #
jarque.test(resid(maximal.noCor2)) # Not normal
kurtosis(resid(maximal.noCor2))

################################
### Elasticities and graphs ###
################################

# HF elasticity
levels(df$HF)
elast.data <- data.frame(seq(from = (-1), to = 1, by = 0.1))
average <- df %>% group_by(HF) %>% summarise(DRGP=mean(DRGP))
average$HF <-
as.factor(c("01","10","11","12","13","14","15","16","17","18","02","03","04","05","06","07","08","09
"))
average <- average %>% arrange(HF)
names(elast.data)[1] <- "DRGP"
elast.data <- elast.data %>% mutate(
                        population=DRGP*0.0321,
                        HF01=DRGP*(0.0321+0.009), HF02=DRGP*(0.0321-0.023),
                        HF03=DRGP*(0.0321-0.017), HF04=DRGP*(0.0321+0.019),
                        HF05=DRGP*(0.0321-0.019), HF06=DRGP*(0.0321+0.028),
                        HF07=DRGP*(0.0321+0.001), HF08=DRGP*(0.0321-0.007),
```

```
                    HF09=DRGP*(0.0321+0.014), HF10=DRGP*(0.0321-0.005),
                    HF11=DRGP*(0.0321+0.004), HF12=DRGP*(0.0321-0.019),
                    HF13=DRGP*(0.0321+0.002), HF14=DRGP*(0.0321+0.008),
                    HF15=DRGP*(0.0321-0.025), HF16=DRGP*(0.0321-0.007),
                    HF17=DRGP*(0.0321+0.002), HF18=DRGP*(0.0321+0.033)
                    )
average$coef <- c(average$DRGP[01]*(0.0321+0.009),average$DRGP[02]*(0.0321-
0.023),average$DRGP[03]*(0.0321-0.017),
          average$DRGP[04]*(0.0321+0.019),average$DRGP[05]*(0.0321-
0.019),average$DRGP[06]*(0.0321+0.028),
          average$DRGP[07]*(0.0321+0.001),average$DRGP[08]*(0.0321-
0.007),average$DRGP[09]*(0.0321+0.014),
          average$DRGP[10]*(0.0321-
0.005),average$DRGP[11]*(0.0321+0.004),average$DRGP[12]*(0.0321-0.019),

average$DRGP[13]*(0.0321+0.002),average$DRGP[14]*(0.0321+0.008),average$DRGP[15]*(0.0321-
0.025),
          average$DRGP[16]*(0.0321-
0.007),average$DRGP[17]*(0.0321+0.002),average$DRGP[18]*(0.0321+0.033))

elast.data %>% ggplot(aes(DRGP, population)) +
 geom_line(linewidth = 1.5, color = "blue") +
 geom_line(aes(y=HF01), alpha = 0.8) + geom_line(aes(y=HF02), alpha = 0.8) +
geom_line(aes(y=HF03), alpha = 0.8) +
 geom_line(aes(y=HF04), alpha = 0.8) + geom_line(aes(y=HF05), alpha = 0.8) +
geom_line(aes(y=HF06), alpha = 0.8) +
 geom_line(aes(y=HF07), alpha = 0.8) + geom_line(aes(y=HF08), alpha = 0.8) +
geom_line(aes(y=HF09), alpha = 0.8) +
 geom_line(aes(y=HF10), alpha = 0.8) + geom_line(aes(y=HF11), alpha = 0.8) +
geom_line(aes(y=HF12), alpha = 0.8) +
 geom_line(aes(y=HF13), alpha = 0.8) + geom_line(aes(y=HF14), alpha = 0.8) +
geom_line(aes(y=HF15), alpha = 0.8) +
 geom_line(aes(y=HF16), alpha = 0.8) + geom_line(aes(y=HF17), alpha = 0.8) +
geom_line(aes(y=HF18), alpha = 0.8) +
 geom_vline(xintercept = mean(df$DRGP), color = "red") +
 geom_point(data = average, aes(DRGP, coef), color = "red", size = 1.4) +
 labs(title = "Hospital averages of DRG elasticity to profit", y = "Elasticity", x = "DRGP") +
 theme_bw()
```

```
# Testing covariate interaction with time
anova <- aov(lnAdm ~ DRGW*Year, data = df) # No significant interaction
summary(anova)
anova2 <- aov(lnAdm ~ DRGP*Year, data = df) # Significant interaction
summary(anova2)

plot(df$DRGW, resid(maximal.noCor2), xlab = "Fitted values", ylab = "Residuals") # Residuals are heteroscedastic
plot(df$DRGP, resid(maximal.noCor2), xlab = "Fitted values", ylab = "Residuals") # Residuals are heteroscedastic
Model.F <- lm(resid(maximal.noCor2) ~ DRGW, data=df)
summary(Model.F)
anova(Model.F)
Model.F2 <- lm(resid(maximal.noCor2) ~ DRGP, data=df)
summary(Model.F2)
anova(Model.F2)
Model.F3 <- lm(resid(maximal.noCor2) ~ lnAdm, data=df) # Residuals dependent on the dependent variable
summary(Model.F3)
anova(Model.F3)

# > anova(Model.F)
# Analysis of Variance Table
# Response: resid(maximal.noCor2)
# Df Sum Sq  Mean Sq F value Pr(>F)
# DRGW         1    0.0 0.000000       0      1
# Residuals 35354 1568.1 0.044354
# > anova(Model.F2)
# Analysis of Variance Table
# Response: resid(maximal.noCor2)
# Df Sum Sq  Mean Sq F value Pr(>F)
# DRGP         1    0.0 0.000000       0      1
# Residuals 35354 1568.1 0.044354
# > anova(Model.F3)
# Analysis of Variance Table
# Response: resid(maximal.noCor2)
# Df  Sum Sq Mean Sq F value    Pr(>F)
# lnAdm        1   38.18  38.185  882.39 < 2.2e-16 ***
#   Residuals 35354 1529.92   0.043
# ---
#   Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```