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Impact of COVID-19 Pandemic on Modelling of Energy Demand

Bachelor's thesis

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COVID-19 pandeemia mõju energianõudluse modelleerimisele

Bakalaureusetöö

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Author's declaration of originality

I hereby certify that I am the sole author of this thesis. All the used materials, references to the literature and the work of others have been referred to. This thesis has not been presented for examination anywhere else.

Author: Lauri Kadakas

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Abstract

The purpose of the thesis is to determine the impact of the COVID-19 pandemic on modelling of energy demands, implement a regression model that eliminates weather effect as a consideration when observing energy consumption changes for business and private consumers, and analyse the results of the model.

Estonian counties are observed during a three-month period, from March to May, to figure out the impact COVID-19 pandemic and lockdown had on energy consumption for business and private consumers, with an overall aggregate is further observed during June and July.

The overall drop in consumption in Estonia was -15% during March and it lowered even more during April but showed a recovery in May and the following summer months. This trend is compared to statistical data and reports from Statistics Estonia and Ministry of Finance.

This thesis is written in English and is 43 pages long, including 7 chapters, 18 figures and 1 table.

Annotatsioon

COVID-19 pandeemia mõju energianõudluse modelleerimisele

Lõputöö eesmärgiks on selgitada välja COVID-19 pandeemia mõju energianõudluse modelleerimisele, mille käigus implementeeritakse regressioonimudel, mis elimineerib ilma mõju, kui vaadelda energiatarbimise muutusi äri- ning eratarbijatel. Mudeli tulemused analüüsitakse.

Eesti maakondi vaadeldakse kolme kuu perioodil märtsist maini, et välja selgitada, mis oli COVID-19 pandeemia ja riigi sulgemise mõju energiatarbimise modelleerimisele nii äri- kui eratarbijatel. Üldine kogulangus Eestis on vaadeldud pikemalt ka juunis ja juulis.

Üldine langus Eestis oli -15% märtsikuus, kuid langes edasi aprillis. Mai jooksul hakkas olukord paranema ja jätkas paranemist suvekuudel. Seda trendi on võrreldud Statistikaameti ning Rahandusministeeriumi statistikate ning aruannetega.

Lõputöö on kirjutatud inglise keeles ning sisaldab teksti 43 leheküljel, 7 peatükki, 18 joonist, 1 tabelit.

List of abbreviations and terms

COVID-19	Coronavirus disease 19
GDP	Gross Domestic Product
NOAA	National Oceanic and Atmospheric Administration

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1 Introduction

1.1 Background

On March 11th, the World Health Organisation (WHO) declared the novel coronavirus (COVID-19) a global outbreak [1], and a day after, local transmission of the virus was found in Estonia [2]. On the same day, state of emergency was announced in Estonia, commonly known as 'lockdown'. [3]

One consequence of the COVID-19 pandemic was a significant change in generation and consumption of electricity worldwide, which was also different from country to country depending on their measures taken [4, p. 1]. California and New York in the United States reported a 10% and 12% decrease respectively after a curfew order [5, p. 1]. Similarly, a 10% decrease in electricity demand was reported in Europe [5, p. 1]. Therefore, it became important to study and analyse the impact COVID-19 has had on electricity demand patterns [5, p. 2], as errors in current models can lead to substantial monetary losses in both public and private sectors [4, p. 1].

1.2 Problem

The importance of accurate models became vital for the health of power grids, as unreadiness to account for extreme events like the pandemic can lead to reduced system reliability and resiliency [4, p. 2]. However, it is important especially in cases of extreme health events to have a resilient power grid, as for example hospitals depend heavily on electricity [6, p. 8]. Knowing how electricity demands change during such events help with maintaining a reliable power grid [5, p. 2].

It is established that seasonal and meteorological changes also affect electricity demand and need to be considered when developing newer models [7, p. 7]. Observed anomalies in energy consumption and behavioural patterns have been guessed to be due to weather changes in some cases [4, pp. 3, 4], yet probabilities are not effective in determining what the impact of COVID-19 pandemic has been on current models of energy consumption.

Therefore, to observe what the impact of COVID-19 pandemic has had on current models became a question of also considering weather changes and behavioural patterns such as holidays or measures taken to combat the virus in a particular country. It is also important to consider private and business consumers separately, as their behaviours in energy demand can be different depending on measures taken.

1.3 Methodology to eliminate the effects of weather

As weather is an important part for models of energy demand, it is interesting to consider if it is possible to eliminate this part to compare periods of time and forecasts of energy demand more accurately. This could help in understanding the effects COVID-19 had more directly on energy consumption, as in many current studies, some dips in energy demand have been surmised to be due to weather, however it is not concrete.

At the Cybernetics Institute of Tallinn University of Technology (TalTech), Professor of Physics Jaan Kalda developed a regression model to determine the effect weather has on energy consumption. It is a multiple linear regression of ten fits: days of the week, a thermal index, usable daylight, and wind chill.

Each day of the week is represented as a stream of numbers of either 0 or 1, corresponding with the day (e.g., Monday would be 1000000, Tuesday would be 0100000, Sunday would be 0000001), and if the day is a state holiday, the 1 would be changed to 0.9. This essentially helps to account for how much of usual demand there is in a day, as on a state holiday, the demand is lesser (thus demand could be 90% or lower of the usual), depicting shortened work hours.

Thermal index is calculated with data from a weather station[8] and solar calculation data from National Oceanic and Atmospheric Administration (NOAA) [9]. The solar calculation data has hourly data and several calculations, among which is Solar Elevation corrected for atmospheric refraction. Kalda theorised the incoming solar radiation should depend on it as a sine function; and because of the inhibitory effect of cloudiness, this is also multiplied by the cloudiness index. Solar radiation is used in combination with temperature to calculate the thermal index, where additionally considerations are made on behavioural patterns of heating and cooling systems.

Usable daylight is also calculated with data from NOAA, where certain hours of the days have different weights under the assumption that earlier hours of the day have less impact. Wind chill however only uses data from the weather station, where it is calculated as difference between the temperatures inside and outside, multiplied by the root of the wind speed. This is because if the heating systems are weak or non-existent, wind chill can also become a factor for heating systems.

1.4 Purpose

By removing the weather effect as a consideration on data, it is clearer to see what the different effects of the pandemic restrictions have had on energy demand and consumption. This in return will help with quantifying the effects COVID-19 has had on existing models.

As J. Kalda has developed his regression analysis in Excel, it has some limitations on data processing and wrangling and thus, it became a necessity to have his methodology present in code. For this reason, the language R was chosen to implement the regression analysis and then observe and analyse the results.

The primary objectives of this thesis thus were:

- Implement J. Kalda's regression analysis in R.
- Analyse the results from the regression analysis.
- Quantify the effects COVID-19 has had on energy demand and consumption.

After that, the secondary objectives of this thesis became:

- See whether the measures taken to combat the pandemic were adequate.
- Compare the Bank of Estonia's reports with results from analysis.
- Code that gives real-time reports on COVID-19 effects is created.

1.5 Overview of the thesis

In the beginning, the methodology idea is outlined with the purpose of the thesis. Afterwards, an overview is presented on current research on pandemic and how energy modelling is impacted by it.

Then, the methodology is explained and an overview on used datasets is given, alongside with used tools and programs.

Afterwards, the results from the methodology are presented, first in an overview of the general change in energy consumption for Estonia, and then for each county specifically. The results are summarised in the end.

In the analysis, obtained results are compared to statistical data from Statistics Estonia and Ministry of Finance, found patterns are outlined and an overall analysis of the results and measures taken is done.

Finally, further ideas on development and the conclusion are given. The thesis summary is also presented.

2 Current research on the pandemic and modelling

This part outlines current research done on the pandemic and the impact it has had on energy consumption and modelling.

2.1 Existing models

In modelling of energy demand, there are three main categories of models – Artificial Neural Network (ANN) models, Linear Regression (often Multiple Linear Regression (MLR) models) [10], and hybrid versions of the two [11].

Specifically for considering the impacts the COVID-19 pandemic has had on several current models, elaborate models have been developed to account for severe health events and crises like the pandemic and subsequent lockdown measures, such as a hybrid multi-objective optimizer-based model ICEEMDAN-MOGWO-SVM[11], which showed great accuracy in its short-term electricity demand modelling.

2.2 Impact of the pandemic on energy consumption

One research has observed the COVID-19 pandemic-related electric shortfall in Pakistan to cause a 5.6% GDP loss in 2020 due to incomplete projects, which will increase to 10.3% by 2028.[12, p. 9]. The research also mentions some other literature that suggests a relation between GDP and energy consumption: as GDP increases, so does energy consumption and vice versa.[12, p. 3]

Other investigations on the impact of COVID-19 pandemic on energy consumption have been in Jordan[5, p. 3], where a separate rolling stochastic Auto Regressive Integrated Moving Average with Exogenous (ARIMAX) model is created. This research analyses the impact the pandemic has had on Jordan’s power grid, including a reduction in average energy consumption of 40% in 2020 compared to 2019.

In one study, it is brought out that the full lockdown in Italy caused a 25% decrease in energy consumption, 13.5% in Spain, and 14% in the state of Ontario (Canada). Kuwait experienced a 17.6% reduction in energy consumption, and several regions in Brazil have seen 20% to 7% reductions depending on region as well.[13, p. 2]

In the same study, residential and non-residential clients are considered from a town in Spain and shown that their behaviours are different, where residential clients show an increase of 13.1% in consumption during lockdowns and non-residential clients had a reduction of 35.2% in consumption.[13, pp. 6, 11]

[14] compares energy consumption data in the US from 2019 and 2020, finding lower consumption all around, citing probable weather differences. To account for that, the study focuses on Gainesville Regional Utilities (GRU) in Florida and applied a weather correction method. The study found a 10% increase in the city of Alachua, which is in GRU territory, offering the stay-at-home orders causing residents to work from home as the reason. As GRU has a lack of large industries, the increase of consumption from residents offset the electricity consumption of commercial buildings [14, p. 11].

The importance of maintaining system stability in an electricity grid is brought out in [15], through flexibility and grid frequency, comparing German and several other European electricity systems during the pandemic. COVID-19 pandemic caused a decline in energy consumption and thus, an increased share of Renewable Energy Sources (RES), which decreased the supply-side flexibility. However, despite the pandemic, the analyses presented show no threat of a blackout in European systems and the grid stability remained high.

[16] compares different consumption profiles from Spain, Italy, United Kingdom, Belgium, the Netherlands, and Sweden, where several countries had strict restrictions and some others, like Netherlands was laxer and Sweden had no drastic measures like lockdowns. Sweden and Netherlands thus had an increase in consumption whereas countries that had stricter restrictions saw a decrease. Therefore, which measures are taken directly affect energy consumption profiles

2.3 Conclusions

- Existing models already consider weather in their predictions for a more accurate result.

- Some more complex models have been developed to also account for severe health events like the COVID-19 pandemic, where several countermeasures have been taken.

- Several countries experienced varying degrees of energy consumption reduction due to the pandemic measures taken. This in the case of Pakistan has led to direct loss in GDP and proposes a direct relation between GDP and energy consumption, at least in the country of Pakistan.

- Maintaining grid stability is important, in which modelling energy consumption is also important. However, while the European systems were affected by the pandemic, they were not at risk of blackouts during lockdowns and instead only saw an increased share of Renewable Energy Sources.

- Countries with laxer restrictions (or almost none) experienced a softer impact from COVID-19, and in the case of Sweden – even an increase in energy demand. Therefore, which measures taken directly affect energy consumption and should be considered in modelling of energy demand.

3 Method

In this part, an overview is given on used datasets, methodologies and tools used to achieve the results.

3.1 Overview of the datasets

Three datasets were used in this thesis: a weather dataset, an electricity consumption dataset from Elektrilevi OÜ, and the solar calculations from National Oceanic and Atmospheric Administration (NOAA). An overview is given on how the datasets were obtained and the quality of the data within.

3.1.1 Weather dataset

The weather dataset is obtained from a public weather station in Tallinn Airport between years 2019 and 2020. The website the weather dataset was downloaded from allowed for Excel format, which was chosen for easier observation of the data. [8]

The weather dataset provided a variety of different information from temperatures to pressures and dew points, but for the purpose of this thesis, the necessary fields were the times of observation, air temperature at 2 metre height from Earth's surface, mean wind speed, and total cloud coverage.

Upon closer inspection, not always was information present. For example, on some days there were several hours missing from the recorded data, therefore the entire row would be missing. In some other cases, only select fields were missing from a particular hourly observation. When entire hours were missing from the dataset, the missing hours were filled in with approximations of what the values should have been by following the trend of nearby values. Similarly, when only a certain field of information was missing, it was filled in to fit the nearby data.

It is possible that from private weather stations, such information might not have those slight inaccuracies, but for the scope of this thesis, public weather stations were accurate enough to have those inaccuracies corrected and not have any meaningful impact on the regression analysis.

3.1.2 Elektrilevi electricity consumption dataset

The electricity consumption data was provided by Elektrilevi OÜ to Tallinn University of Technology for study and research purposes under agreement JV-ARI-18/27941. This information is not publicly available.

The electricity consumption dataset is a collection of daily measurements of electricity consumption from different locations in a granular form. The data also includes flags for whether the data was from business or private consumers. This was later aggregated together for each county and the type of consumer.

The measurements had a few curious observations, such as one on 8th of July 2020, where several locations reported a vastly higher amount of electricity consumption. This was considered as an error in observation and instead, the entry for the day was replaced with the average of the next and previous day. It is still possible there are other smaller inaccuracies present, however.

3.1.3 Solar calculations from NOAA

The solar calculations obtained from National Oceanic and Atmospheric Administration were necessary for Kalda's regression model and did not have any entries missing from data.

3.2 Tools and programs used

3.2.1 Programming language

R is a programming language and environment for statistical computing and graphics, providing a wide variety of statistical and graphical techniques, such as linear and nonlinear modelling, time-series analysis. Because of its convenience and ease of linear modelling, this language was chosen for the purposes of this thesis.[17]

3.2.2 R Libraries for data processing

Additionally, R is extended by many other libraries, offering more in-depth tools for any task. Tidyverse is a highly popular collection of different packages and libraries, offering several tools for better data visualisation, handling, and processing.[18]

The zoo library in R was also used for the ease of calculating rolling means of some data.

3.3 Overview of the methodology

3.3.1 Aggregation of current datasets

In the beginning, datasets needed to be transformed into usable formats. The electricity consumption datasets were thus presented in the format to give a clear overview of aggregated consumption data for each county, differentiated by private and business consumers. This allowed for easier analysis for each separate county, and also to see how the differences in private and business consumer behaviour affected consumption and modelling.

The weather datasets, after processing the data and correcting any missing entries, were shortened to only use necessary fields for the calculations of regression fits. Because the electricity consumption is given for each day, not each hour of the day, the fits were also aggregated as overall means of each day.

3.3.2 Creation of the day fit

An additional dataset was created in the form of a data frame of seven columns corresponding each day. For each row of the day, the matching weekday was assigned value 1 while the others were assigned 0. This was then repeated to create two datasets - one for private consumers and other for business consumers.

Both datasets were iterated on to account for holidays. As it is impossible to predict who is on leave and when, only state holidays were currently used, obtained from Riigiteataja.[19]

The model training used a period of roughly one month, from January 31st to March 3rd, and as such, there was only one important state holiday in the period - February 24th, the day of Independence. Thus, the day fit was adjusted again to consider stronger changes in the behaviour of electricity consumption for both business and private consumers. The adjustment is necessary, because a large spike during the fit period could distort the predicted values of the model.

3.3.3 Linear regression for each county

The R language provides easy functions to calculate linear regression with. In this thesis, the basic *lm* function was used for multiple linear regression (MRD). The regression was performed for each county and consumer type, thirty in total.

From each linear regression, R allows easy access to coefficents of MRD, which were later used to calculate residuals by hand. Those residuals were collected in a separate data frame, where additionally for each day, a seven-day average of residuals were calculated as well. This describes the given period’s average decrease in consumption.

As consumption decreased as a whole, the calculated linear regression did not account for general decrease and thus overestimated the fluctuations from weekly cycles. Kalda assumed that the weekly cycle amplitude is proportional to general consumption and compensated the residuals accordingly.

The compensation was done by subtracting from the given day’s residual the product of the seven-day average and the given day’s weighted relative daily fit. The weights for each fit were found through multiplying each fit by the proportion of the seven-day average.

The weighted fits were then used again to find the normalised residuals, following the same process of calculation by hand. However, as the compensation for fluctuations also lost the total decrease in consumption, the previously calculated averages were also added to the residuals. This process was repeated for each county and consumer type as well, and the calculated normalised residuals show the actual change in electricity consumption.

4 Results

In this part, the results of the work are presented. Each county data is observed and summarized in a table. Additionally, the loss in consumption is also visualised for several counties and consumer types. A collective summary of the county changes is presented at the end as a table, with a short overview on the county data that brings out some similarities and differences.

4.1 Overall change in consumption

The overall change in consumption is seen as an aggregate of all county data, comparing the same time period for both years 2019 and 2020. The existing regression model has been used to calculate the normalised residuals for 2019 to show it can predict the values quite well for several months beyond the training period.

The training period was 31 days – from January 1st to March 3rd, after which the model shows good results for up to five or six months, therefore for a general overview of what the change in consumption was, the prediction period was chosen as the period from March 4th to July 31st for about five months in total. The normalised residuals for 2019 and 2020 are plotted together on Figure 1.

The month of July had some consumption measurement errors from Elektrilevi OÜ. The 8th of July error was corrected as it would have skewed the y-axis too high, but there is another jump in consumption on July 23rd and for the following two days. This is currently inexplicable but was left in as the error was not too drastically different from nearby dates.

There are also similar drops for both years on May 1st, which is due to the May Day state holiday. A second drop happens during April 19th of 2019, and April 10th of 2020, which is due to the Good Friday state holiday. The third drop happens from June 22nd to 24th, which coincides with Victory Day and Midsummer Day. However, in 2019, these happened on weekends, therefore their drop was smaller. The final drop is on July 15th and 16th, which currently is also inexplicable.

The normalised residuals during the month of July show a decrease in electricity consumption for 2019, which could be due to the lengthy prediction time period. However, the normalised residuals for 2020 show a smaller decrease, therefore the model currently suggests, that the consumption was starting to stabilise during summer, which coincides with the time when many restrictions were lifted.

For an easier understanding of the general change in consumption, the residuals in 2020 should be subtracted from the residuals in 2019, which is shown in Figure 2. Because the year 2020 was a leap year, the residual for February 28th is recorded twice for the year 2019 as otherwise, it would skew the shown change.

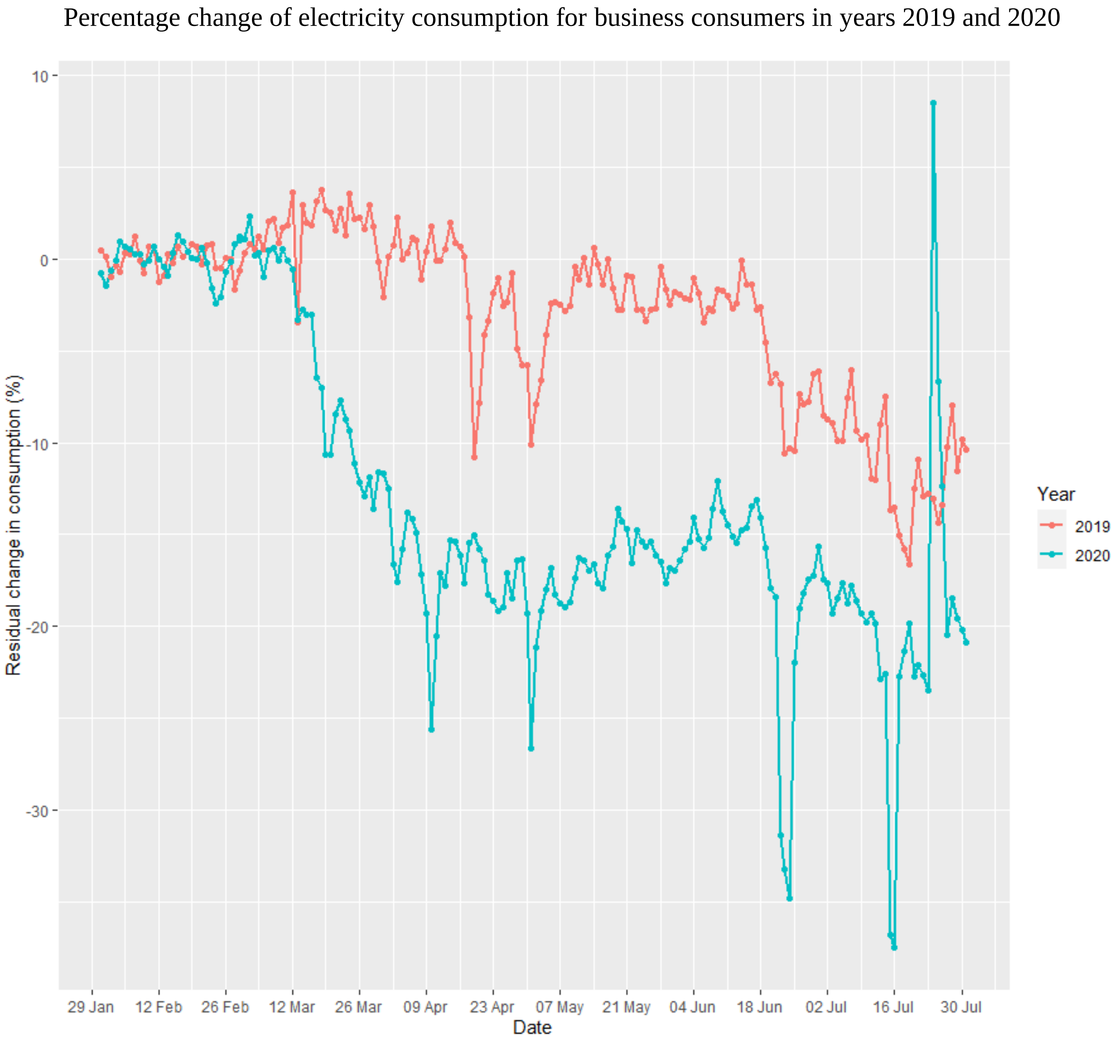

Figure 1. The normalised residuals are plotted together to show their general trend for business consumers.

The difference also accounts for movable state holidays, where the correct date and the surrounding dates are chosen for comparison instead. For example, the Good Friday was on April 19th of 2019 and April 10th of 2020, so the dates April 18th to 20th of 2019 were compared with the dates April 9th to 12th of 2020. Conversely, April 9th to 12th of 2019 was compared with April 18th to 20th of 2020 to account for the missing dates.

From Figure 2, it is clearer to see how the difference lessens as restrictions are lifted, gradually stabilising throughout the summer. There is still a general loss in consumption, which might be due to many still opting to stay at home, work from home, or generally travel less during the pandemic.

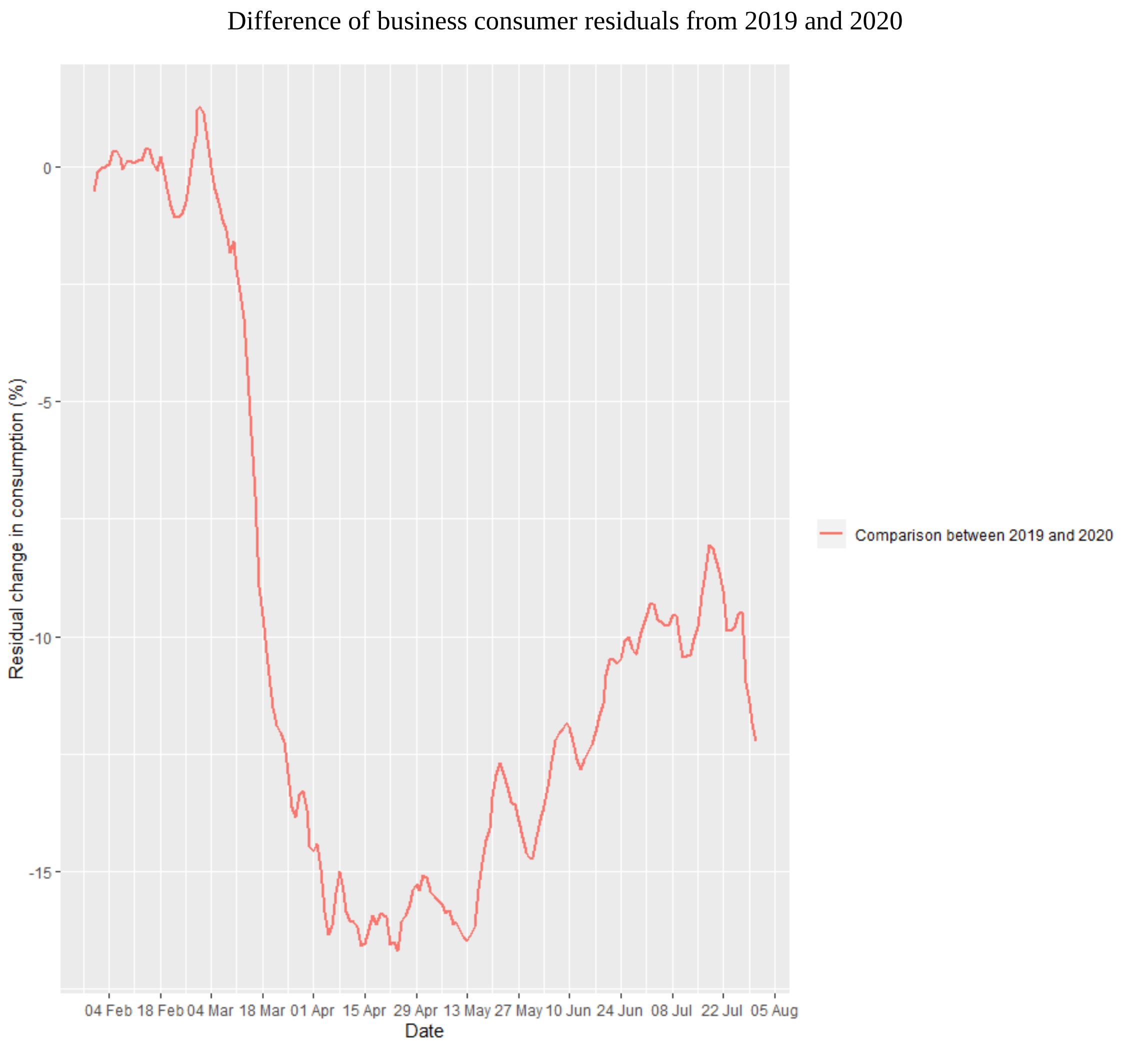

Figure 2. To account for the weekly cycles, an average of the surrounding three days is taken instead for each day, removing smaller spikes seen on Figure 1

4.2 County-specific changes

In this part, only the more interesting changes are brought out for either business or private consumer types. Some counties followed a similar graph to others; therefore, their graphs or overviews are omitted and grouped with other similar graphs. Some counties also had a more detailed analysis due to having more interesting data – whether it was denser in population or had stronger restrictions, or the county was more industrial.

4.2.1 Harju County consumer changes

The change is depicted in Figure 3, with an almost immediate drop in consumption for business consumers a week after the lockdown was announced. Within three weeks, the consumption drops by almost 15% and continues to fall to about -20% in consumption for the duration of April, with the lowest change in consumption excluding holidays being on April 25th at -22.7%.

Figure 4 depicts Harju County's private consumer change. The weekly cycle is more pronounced throughout, with earlier weeks having an amplitude of roughly 12%. The fluctuations stabilise towards the end of the lockdown with an amplitude of 7%. Instead of a constant decrease as seen with business consumers, the lockdown amplified the weekly cycles instead.

However, there is not a large growth in consumption for the duration of stay-at-home orders, peaking at an 8.8% increase on March 18th.

Harju County business consumer change in consumption

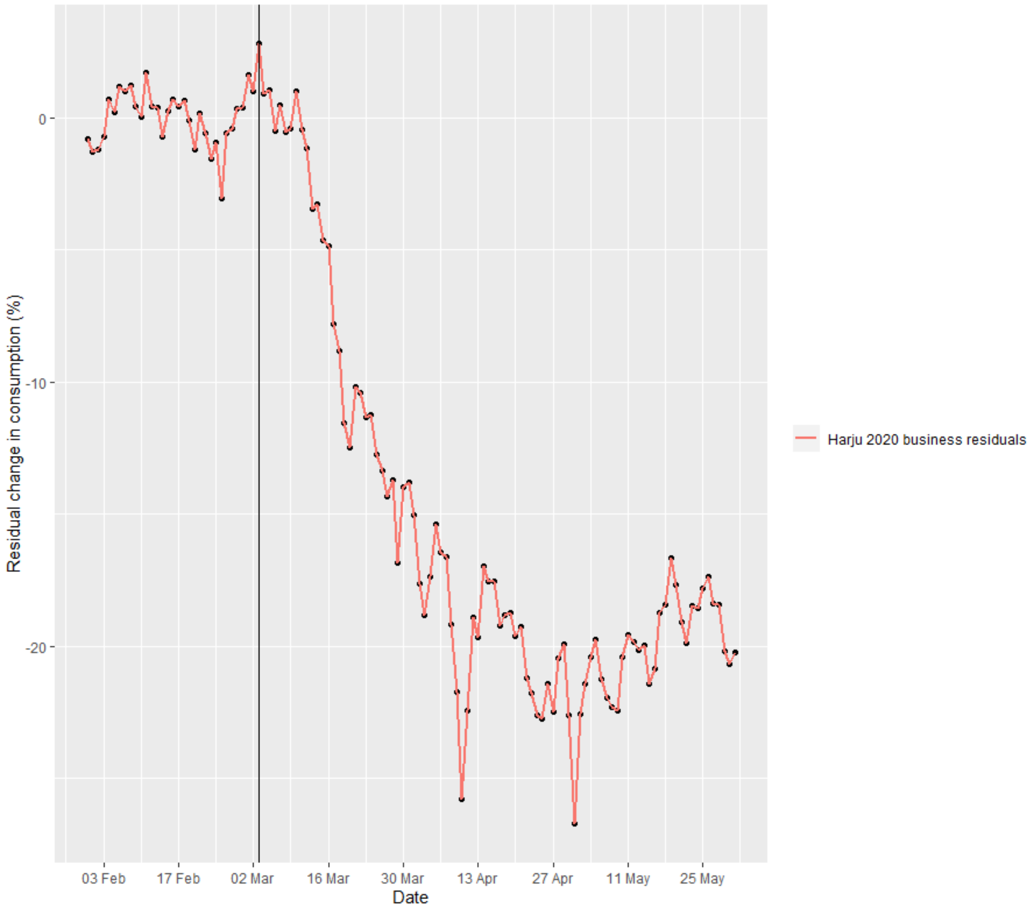

Figure 3. Harju business consumer residuals are plotted for the duration of the lockdown in Estonia, without weekly cycle normalisation.

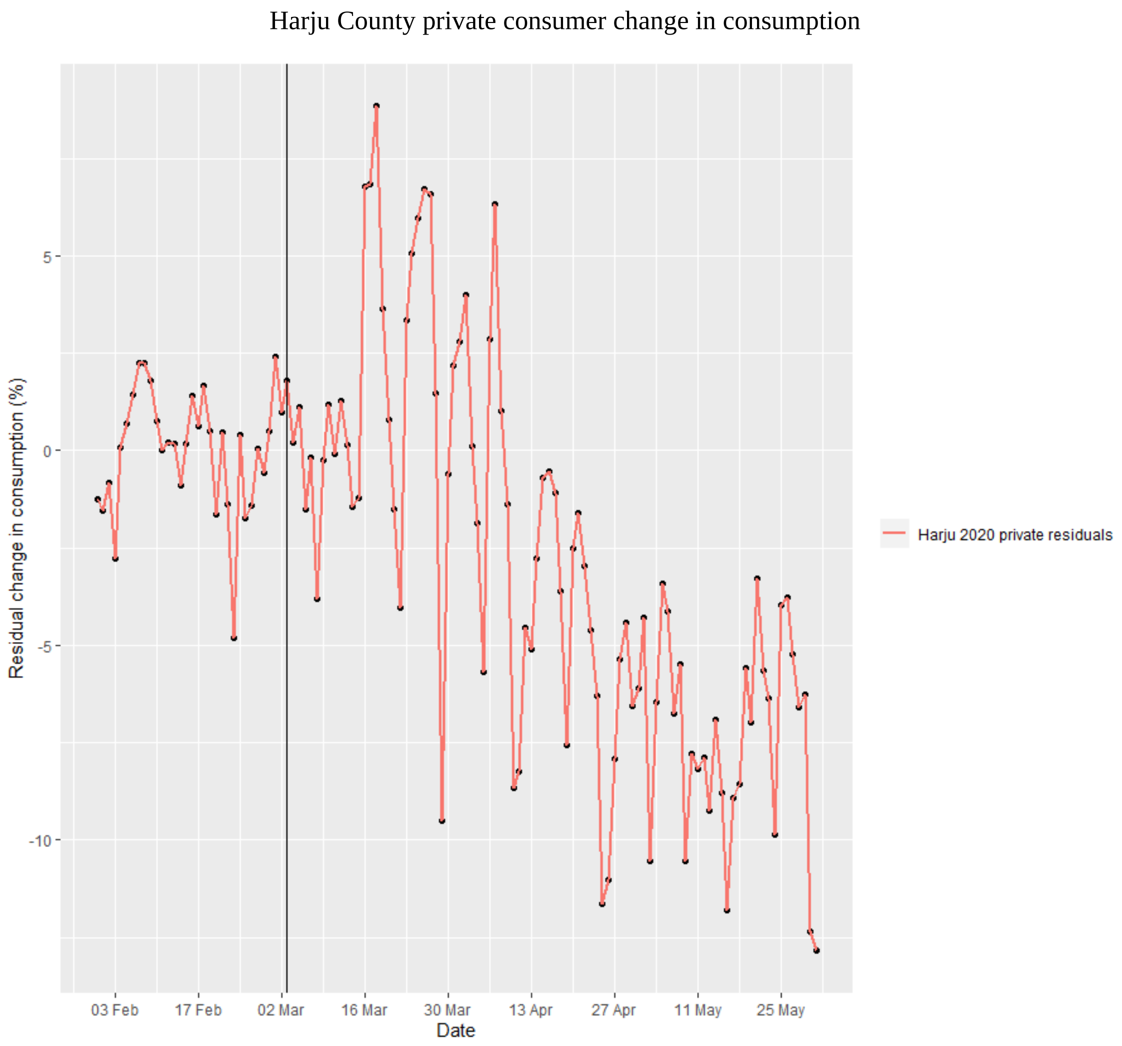

Figure 4. Harju private consumers' weekly cycle shows a larger fluctuation in consumption.

4.2.2 Ida-Viru County consumer changes

The consumption change for Ida-Viru business consumers is shown in Figure 5, where the weekly cycle is more pronounced. There are larger fluctuations, but a general loss is shown, with the earlier weeks fluctuating between -5% and -15%. During the month of April, the consumption stays at a near -30% low. There is a large drop on May Day, but the surrounding days are instead below -20%, so the actual consumption might be not as drastic.

For majority of May, the consumption stays near -20%, with a sudden drop around May 26th to the lowest of the entire lockdown period, -34.5%.

Ida-Viru County business consumer change in consumption

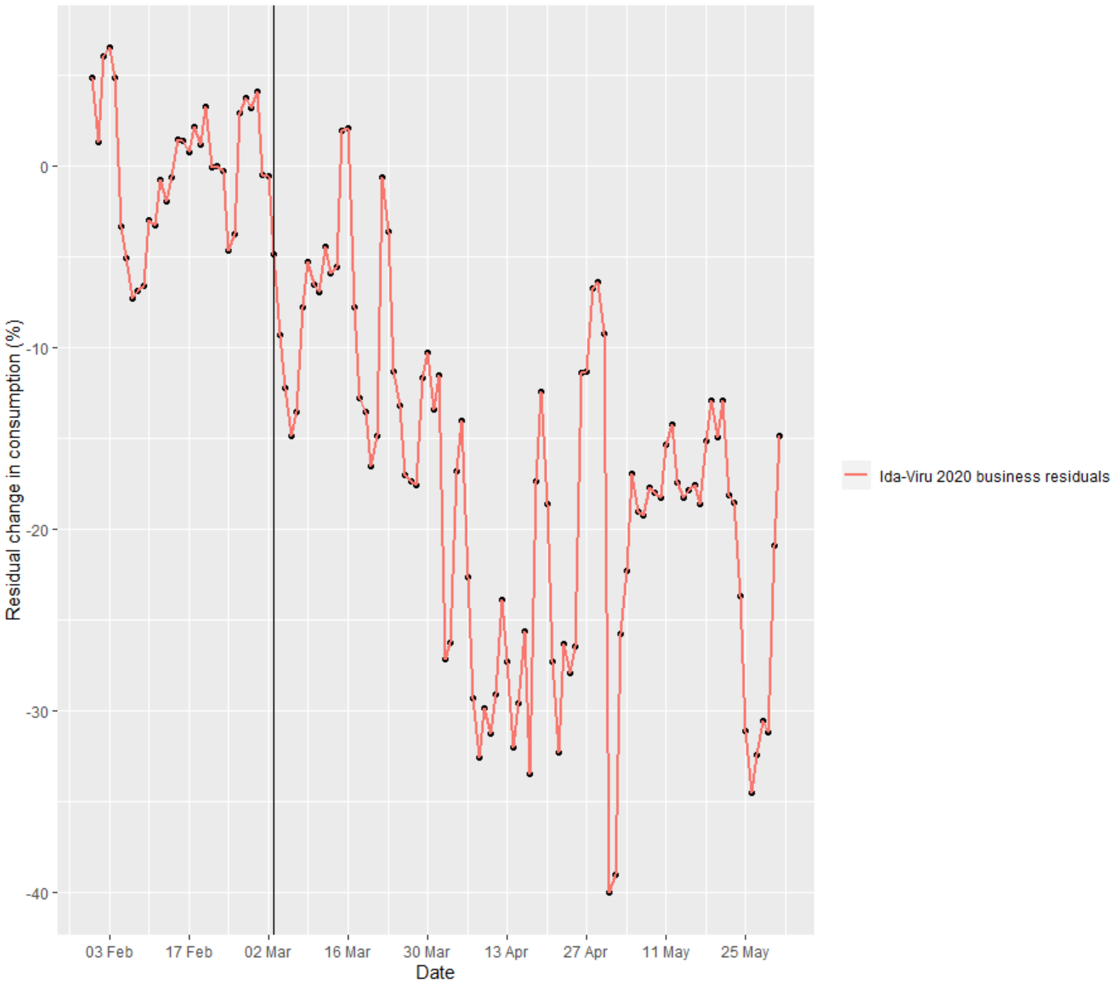

Figure 5. Ida-Viru County business consumers show a larger decrease in consumption, but also has very large fluctuations with an amplitude of nearly 20% for some weeks.

Figure 6 shows the consumption change for private consumers in Ida-Viru County, with a noticeable increase in general during the lockdown period. The largest spike in consumption is on May Day, but outside of state holidays, there are similarly large spikes on other weeks, with the highest being on May 21st, with an increase of 17.3%.

For the most part, electricity consumption rose by about 10% for private consumers in Ida-Viru County with a slight decrease towards the end of lockdown.

Ida-Viru County private consumer change in consumption

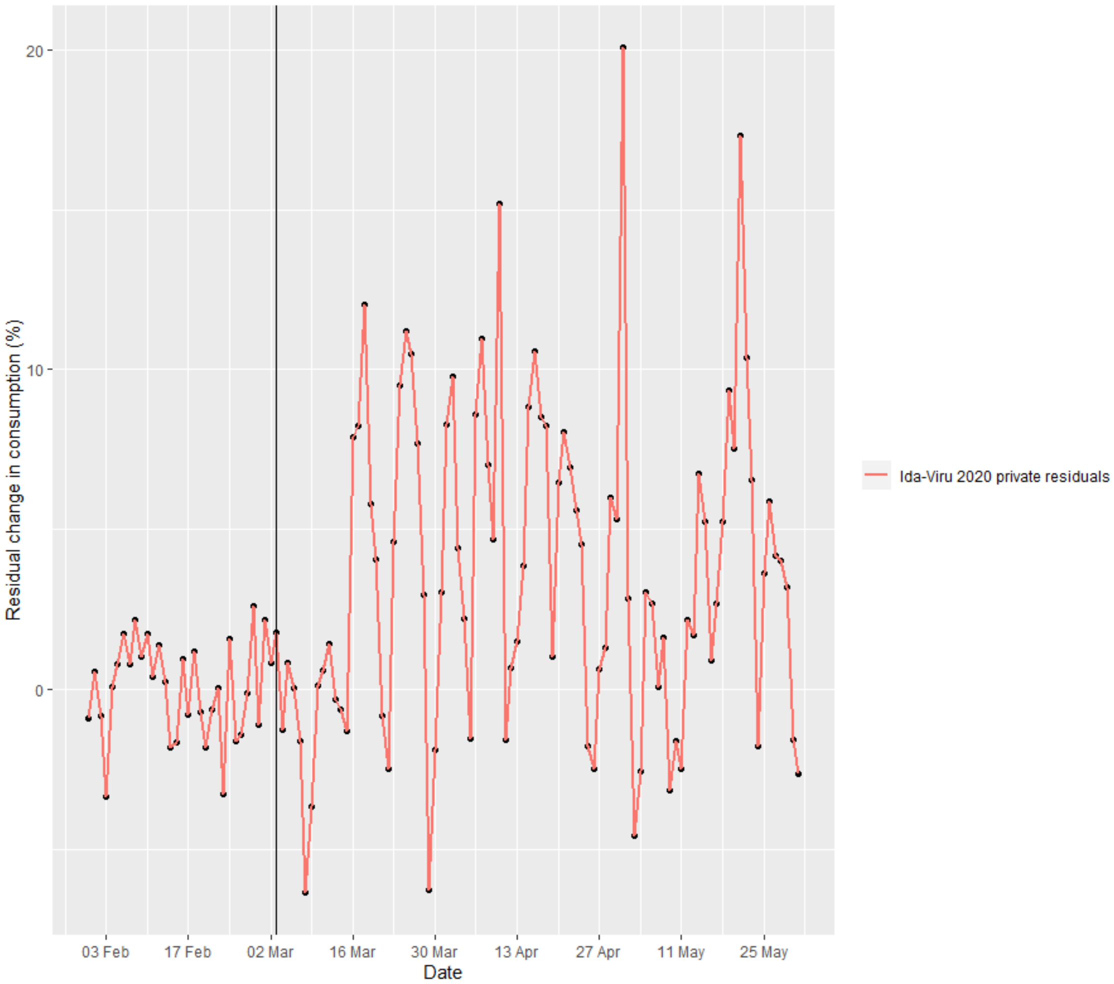

Figure 6. Ida-Viru County shows a weekly fluctuation of about 10%, with some larger spikes of demand inbetween for private consumers.

4.2.3 Lääne-Viru County consumer changes

Lääne-Viru County's private consumer change showed a similar trend to Ida-Viru County's private consumer change, so the graph will be omitted. As a whole, Lääne-Viru private consumers had a lower demand, where the difference with Ida-Viru private consumers was about 5%, with the lowest drops being on March 29th and May 11th with -11.15%, and a high of 9.5% on March 18th.

Figure 7 shows Lääne-Viru County's business consumer changes, with a heavy decline throughout the lockdown. Excluding the state holidays, the lowest points were on May 10th, 24th, and 31st with close to a -35% change in consumption. The consumption does not stabilise towards the end of lockdown, continuing with heavy fluctuations of about 15%.

Lääne-Viru County business consumer change in consumption

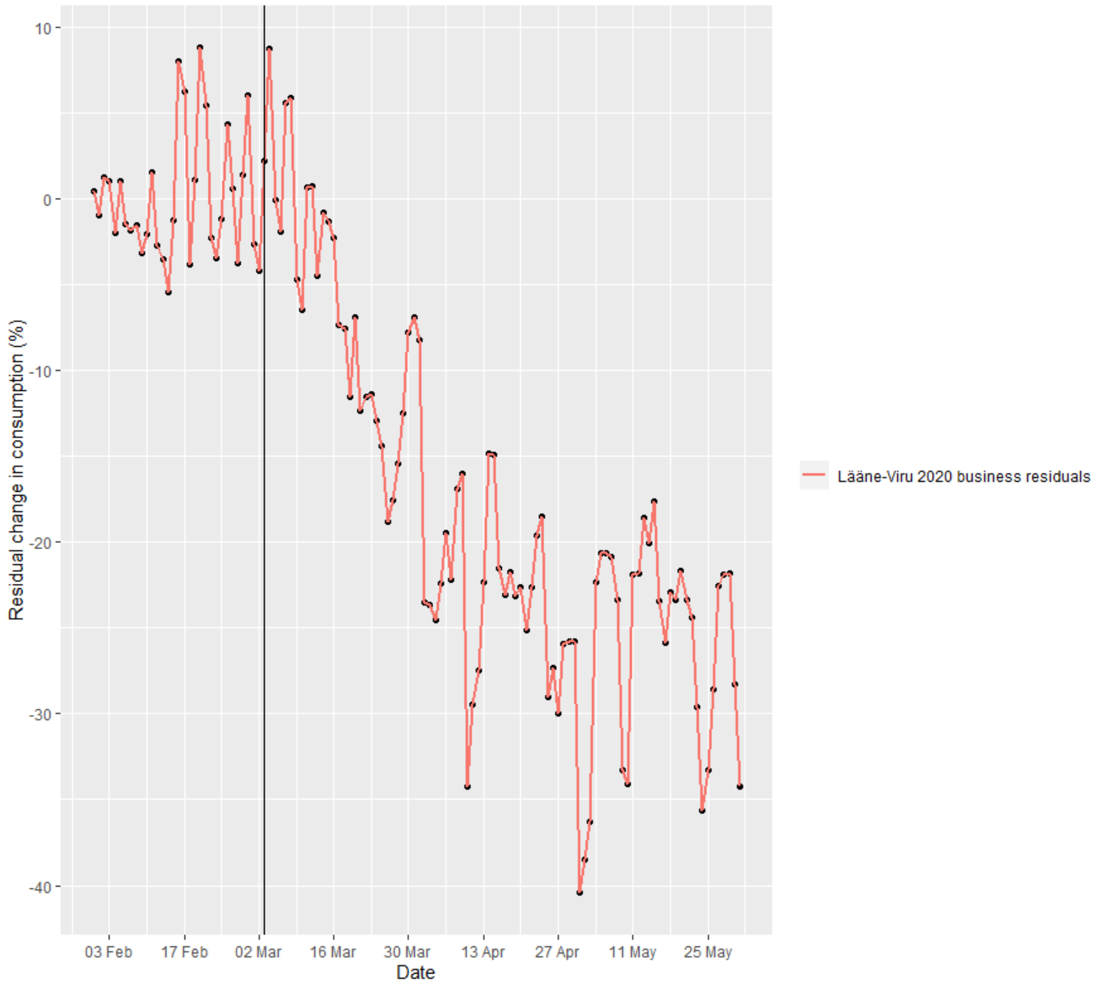

Figure 7. Lääne-Viru business consumers had fluctuating demands throughout April and May, between -20% and -35%.

4.2.4 Saare County consumer changes

The lockdown has a clear impact for Saare County business consumers for the duration of March, shown in Figure 8. The demand stabilised in April and showed a small uptrend throughout May. The first week of the lockdown thus showed the most drastic change, a change from nearly 0 to about -17% in demand. The weekly fluctuations however were smaller for throughout the three months.

Saare County business consumer change in consumption

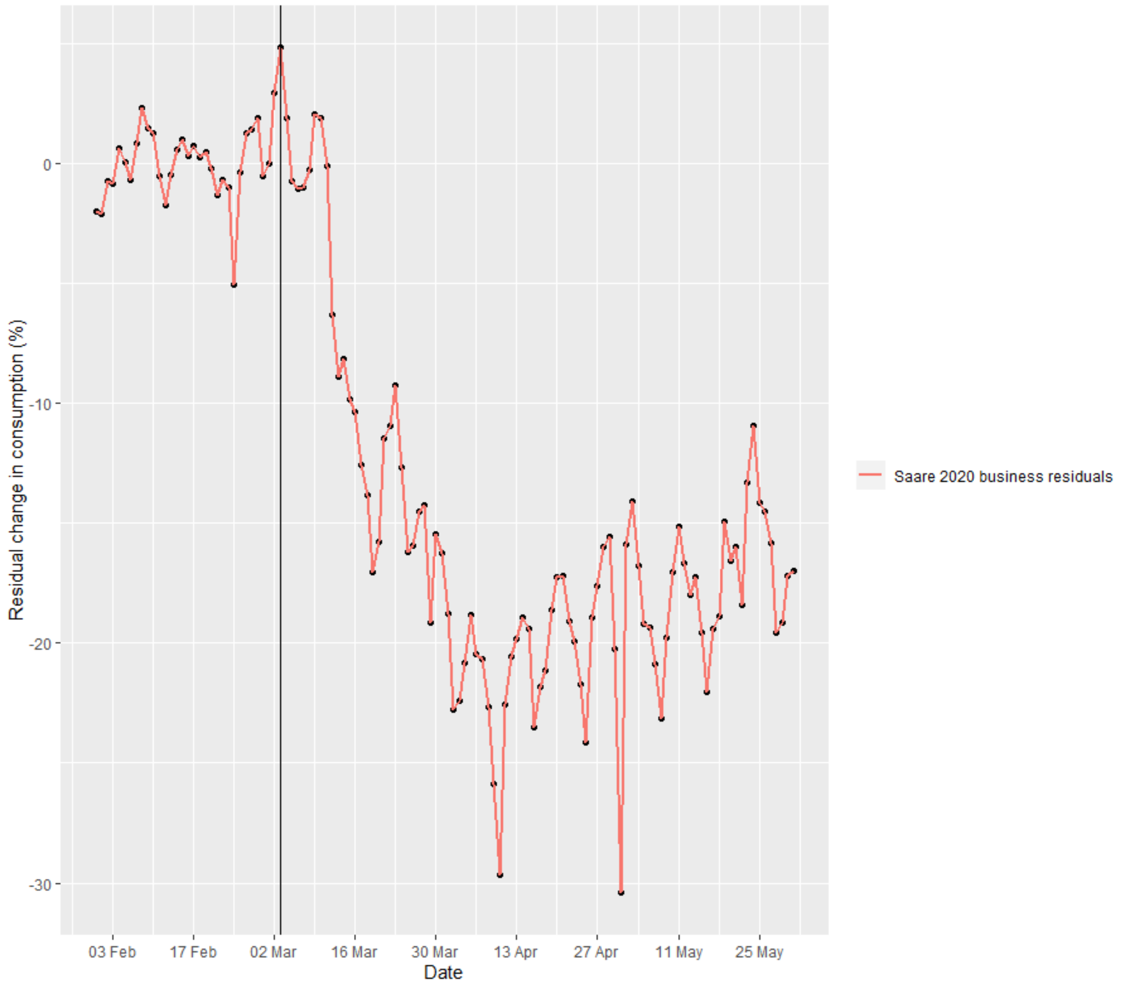

Figure 8. The change in consumption stayed near -20% for most of April, increasing for May.

Saare County was first and hardest to be hit by the COVID-19 virus during spring. While stay-at-home orders were issued, and all Western islands were quarantined[20], there was still a small downtrend in demand for private consumers in Saare County, though initially the demand increased to nearly 10%, immediately after the closure orders.

The increase in demand continued for the rest of March, with high fluctuations in consumption during early April as seen in Figure 9. The demand continued to lower and stabilise throughout April and early May, staying near -10%. The demand increased again at the end of May.

Saare County private consumer change in consumption

Figure 9. Saare private County consumers show high weekly fluctuations during early April, which stabilise by the end of the month.

4.2.5 Hiiu County consumer changes

For the most part, Hiiu County followed the same trends in Saare County, as they were also affected by the quarantining of the Western islands. However, the business consumers stayed stabile throughout March and did not have an immediate drop like in Saare County, and the fluctuations were smaller for private consumer demands.

4.2.6 Järva County consumer changes

Järva County's private consumer changes followed the usual trend with high weekly fluctuations throughout March but stabilise in April and May. However, for the business consumers shown in Figure 10, the decline is steady throughout March and the weekly cycles come in later than in other counties, showing fluctuations throughout April and May.

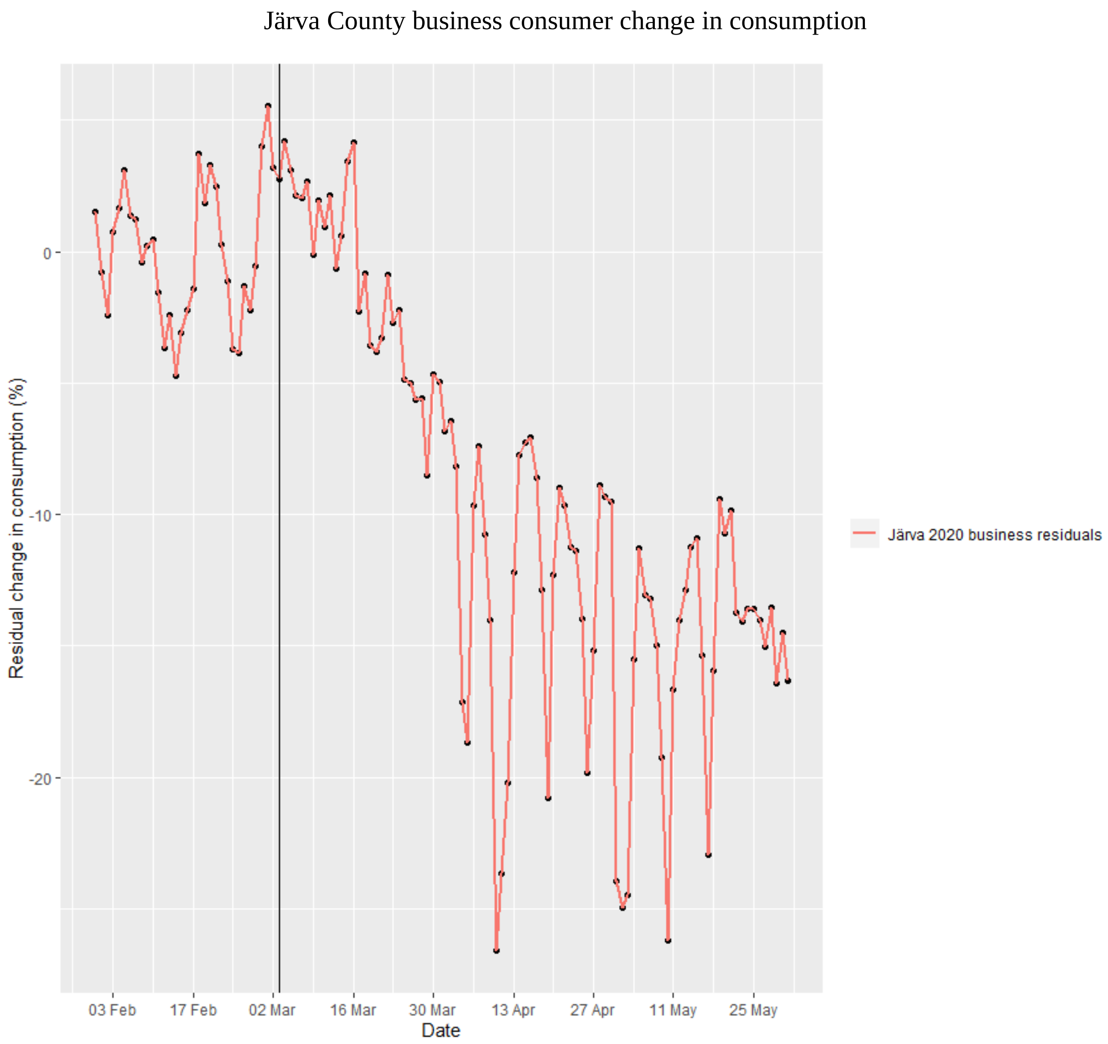

Figure 10. Järva County's weekly cycle comes in during April, fluctuation between -7% and down to -25%.

4.2.7 Lääne County consumer changes

Lääne County consumer data is weaker; therefore, its business and private consumers have high fluctuations that may be due to a company starting work, but no meaningful analysis can be done from its results.

4.2.8 Rapla County consumer changes

Rapla County's business consumers showed a smaller decline than other counties, staying around -7.5% for the duration of April and May. However, Rapla's private consumers showed a general increase or just higher fluctuations in consumption. There was not a clear decline for the private consumers in Rapla, or it was minuscule as seen in Figure 11.

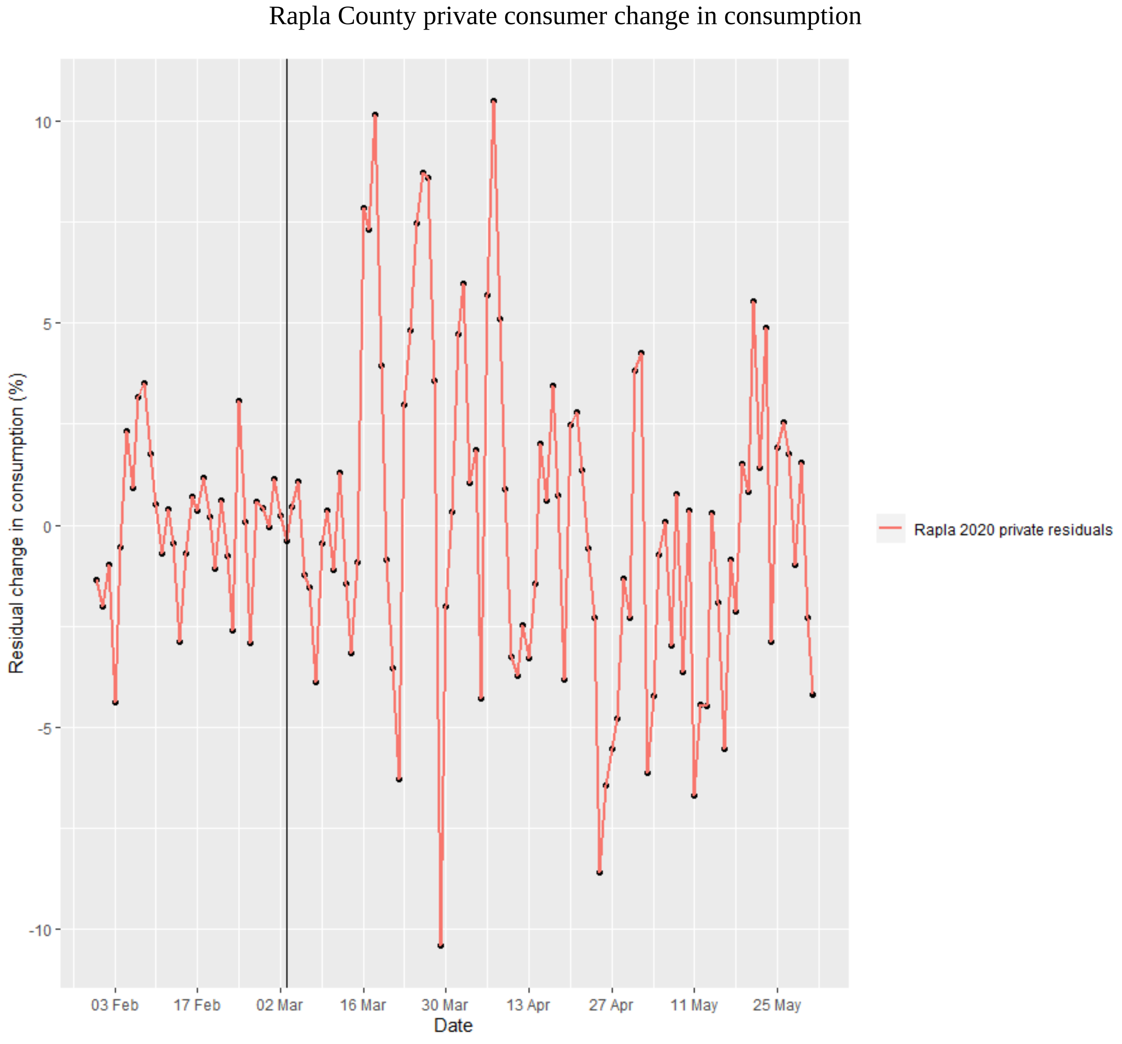

Figure 11. Rapla County's private consumers fluctuated heavily between 10% and -10% in consumption until April 13th.

4.2.9 Jõgeva County consumer changes

The changes in Jõgeva County followed similar trends to other counties, where business consumers declined to near -12.5% during April and May, while private consumers had high fluctuations like Rapla County's, showing similar increases in demand as well.

4.2.10 Pärnu County consumer changes

Pärnu County's business consumers followed the same trend of Saare County's business consumers, but with the small difference of not showing an uptick in demand towards the end of May. The private residuals stabilise quicker and do not fluctuate as much as in other counties during April and May, with a general decline of -10% in consumption, shown in Figure 12.

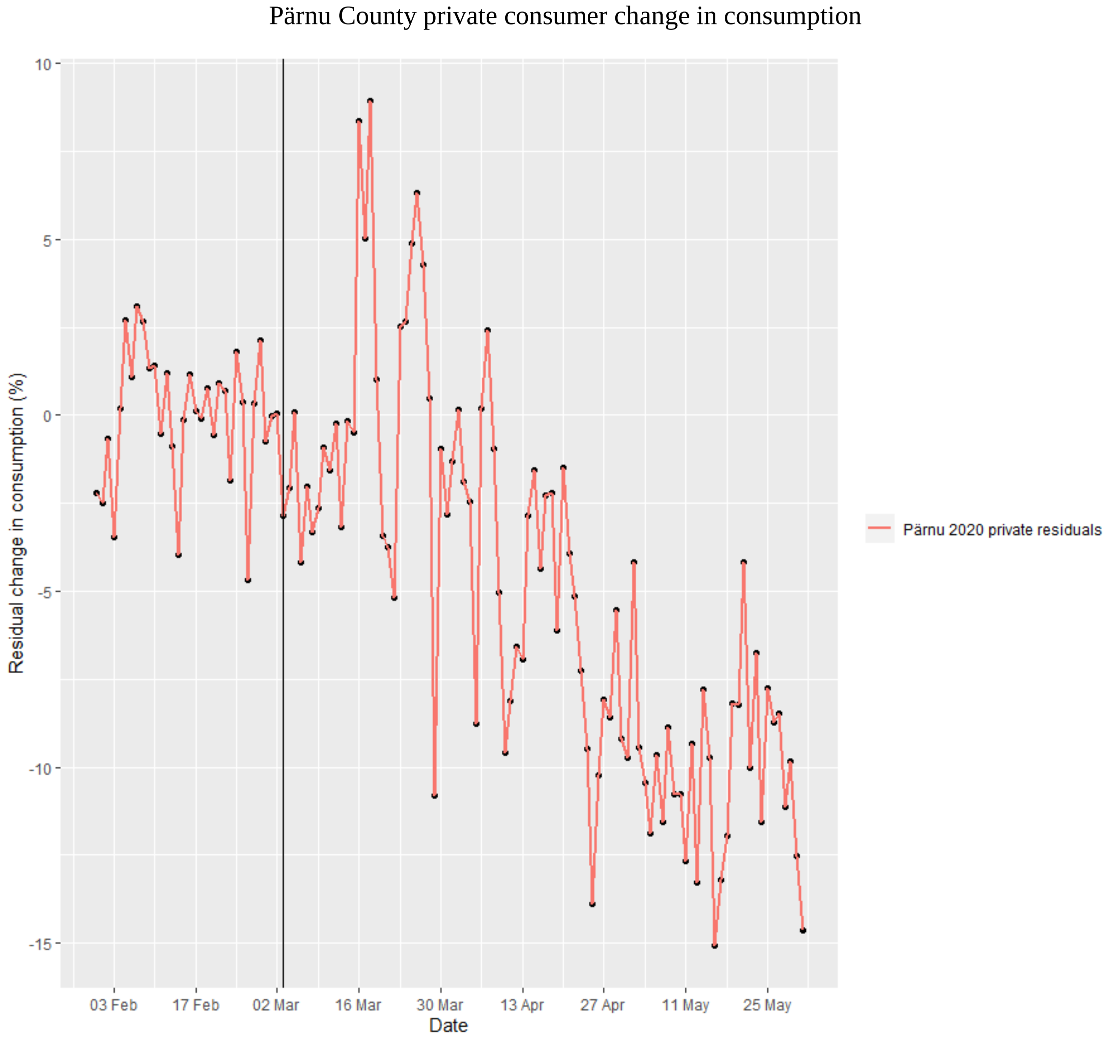

Figure 12. Pärnu private consumers continue with a small general decline in consumption throughout April but jump in demand during May.

4.2.11 Viljandi County consumer changes

Viljandi County's day fits for business consumers showed a large impact from Independence Day, therefore the day fits were changed accordingly from 0.8 to 0.7 for business consumers. Private consumers did not show such an impact, so their day fits were left as is.

The change in consumption for business consumers in Viljandi had a slow decline, stabilising in April and staying near -15%. The weekly cycles come in early, but do not fluctuate as much as in other counties with about 5% in difference, as seen in Figure 13. The two large dips are from state holidays.

Viljandi County business consumer change in consumption

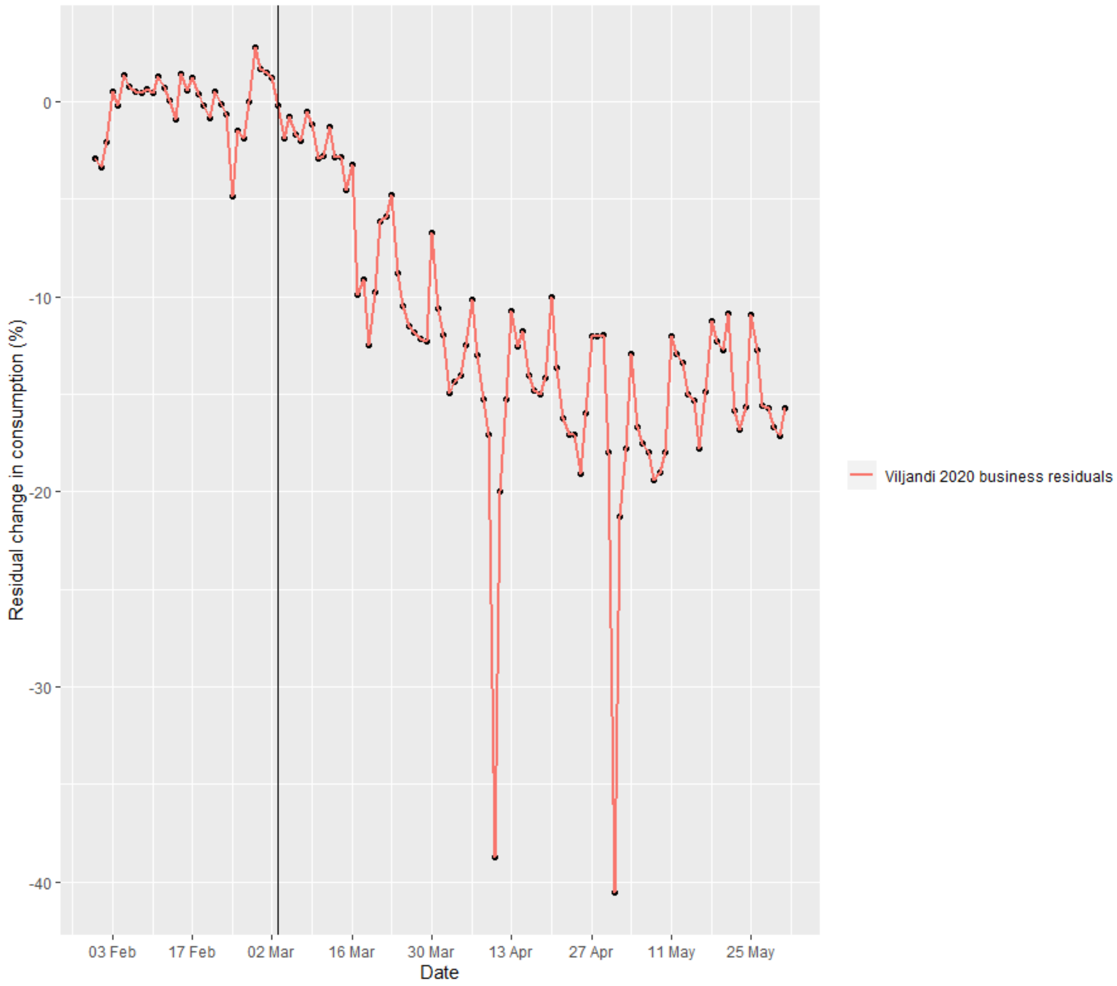

Figure 13. Viljandi County's business consumers show a decline to just around -15% in consumption.

Viljandi private consumer changes fluctuated between 7.5% and -7.5% for the duration of March, lowering in amplitude during April and May. There is a small decline in consumption at start of May where the weekly cycles fluctuate between -2.5% and -10%.

4.2.12 Tartu County consumer changes

Tartu County's private consumers show a similar trend as in other counties, where demand fluctuates between 10% and -5% in consumption change, and a small decline in consumption for the first weeks of May.

Figure 14 shows how Tartu county's business consumers follow a similar trend to Saare County's with an early dip in consumption, the lowest point being at -18.5% on April 3rd excluding state holidays. However, it is interesting that during April and May, there is a clear uptrend in demand, suggesting that perhaps Tartu business consumers managed to recover quicker than other counties in Estonia, ending at just below -5%.

Tartu County business consumer changes in consumption

Figure 14. Tartu business consumer residuals show a quicker recovery from the lockdown measures than in other counties.

4.2.13 Põlva County consumer changes

Similar to Tartu's business consumer changes, Põlva County business consumers showed a quick recovery as well, though they were less impacted and showed a smaller decline in consumption. However, the business consumers showed higher fluctuations in demand, as the weekly cycle is seen throughout the lockdown.

Põlva County's private consumers showed a very drastic increase in demand, spiking very quickly to around 18% in March and increasing throughout April and May. The highest peak was on May 21st with a 24.8% increase in consumption, as seen in Figure 15.

Põlva County private consumer change in consumption

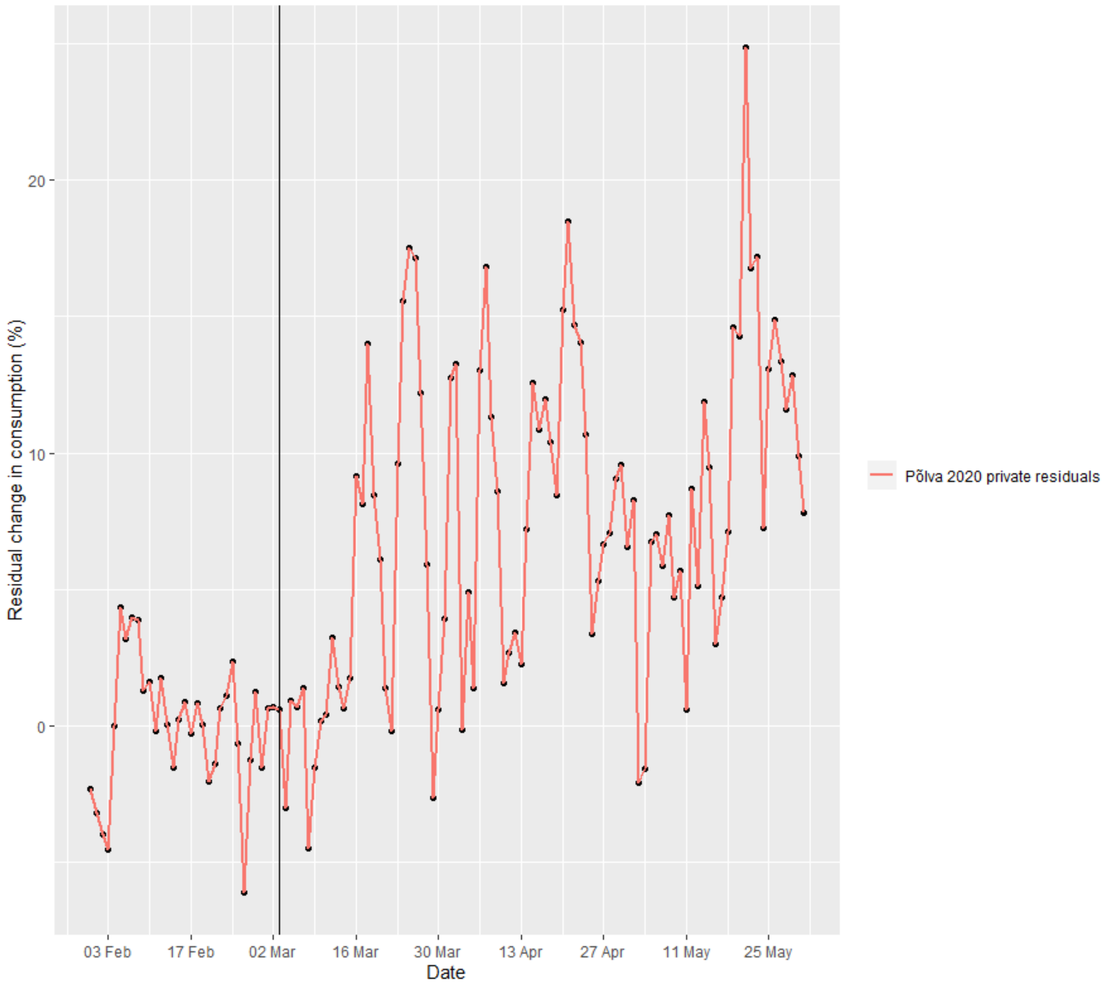

Figure 15. Põlva County's private consumers fluctuate heavily between 0 and around 17% throughout March and April, with a general upwards trend during May.

4.2.14 Valga County consumer changes

Valga County business consumers had a small decline in consumption during March and April, with the worst excluding state holidays being on March 31st with a -9% decline. On the second half of May, Valga County's business consumer however showed a large jump in consumption, as seen in Figure 16, where they average to above a 5% increase in consumption.

Private consumers in Valga County see a similar increase like in other Southern counties with fluctuations up to 12.5% in the weekly cycles.

Valga County business consumer change in consumption

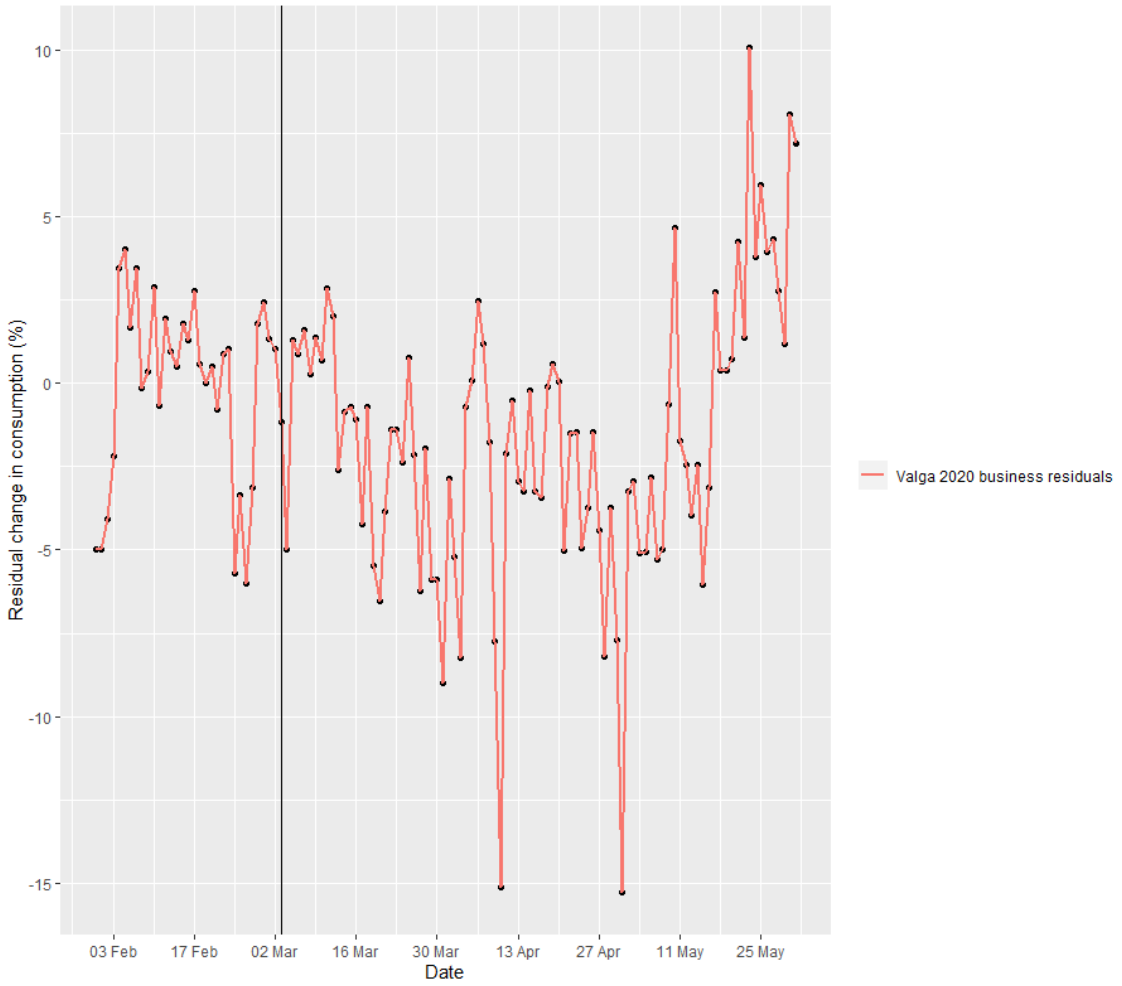

Figure 16. Valga County business residuals did not fall below -10% excluding state holidays.

4.2.15 Võru County consumer changes

Like in other Southern counties, Võru County business consumers were not as severely impacted as in other counties, with a weekly cycle present already in March, but fluctuations staying mostly between 5 and -5% throughout the entire lockdown.

Figure 17 shows Võru County private consumers experiencing a large increase in consumption overall, with highest spikes for all private consumers at 33.6% on April 7th. Similar spikes in consumption repeated on April 20th and 22nd with 31% and 29.3% respectively. Overall, the general increase in Võru for private consumers was near 10%.

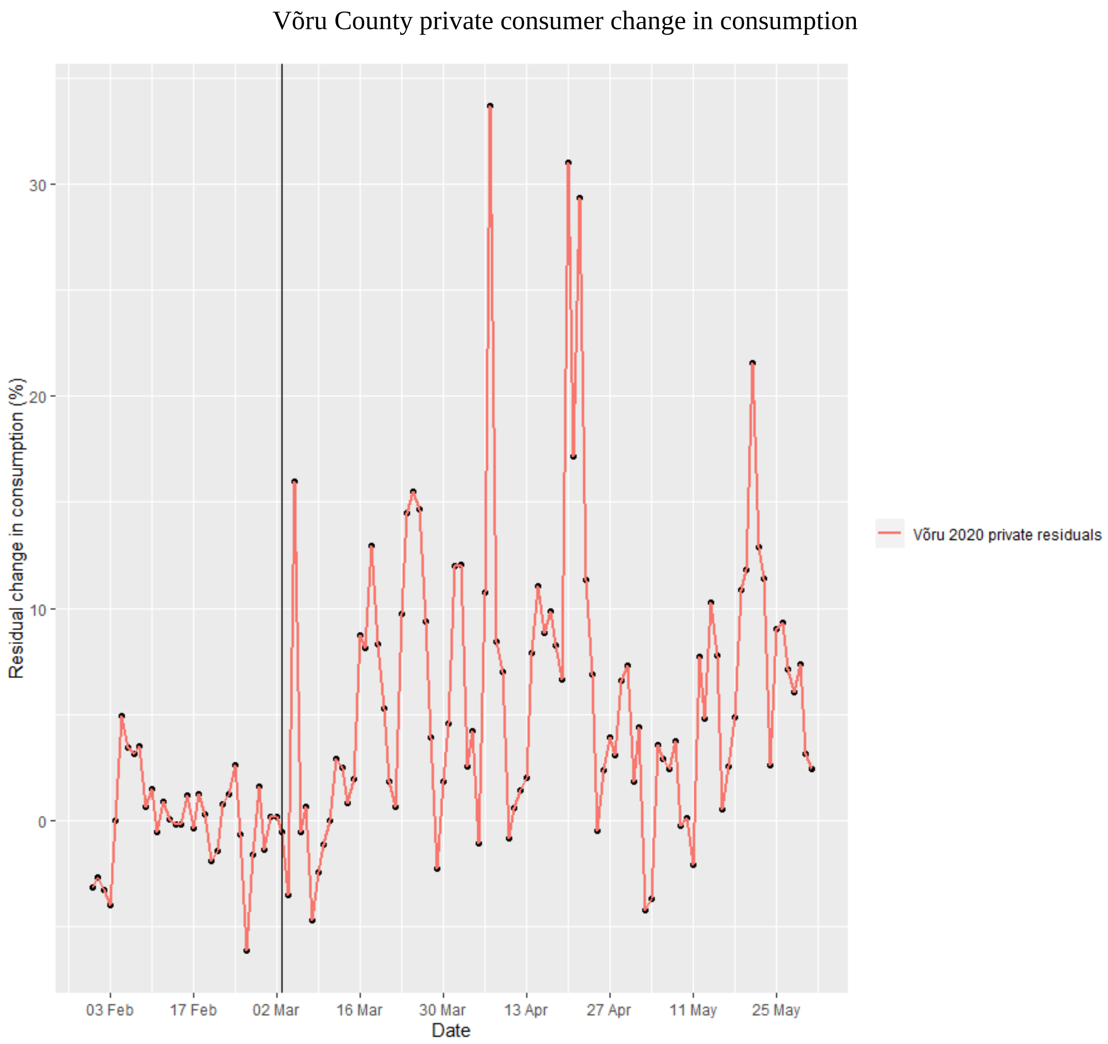

Figure 17. Võru showed a similar trend like in other Southern counties with a large increase in private consumer consumption.

4.3 Summary of county results

The results are summarised in Table 1 for each county's private and consumer data. First, there is an overview of all fields and then, the results are shown in a larger table. In the end, a short summary on the results is also presented.

4.3.1 Overview of data shown

Next to the county and the consumer type is shown the cumulative sum of residuals throughout the lockdown period, which shows the hardest-hit county in terms of decline. Then, the consumption at the beginning of lockdown (calculated as the mean of the fit period) and at the end of the lockdown (as the consumption on May 31st). Lowest consumption during the period is also shown, however for many counties, this can be a state holiday. Finally, an overall change in consumption is shown as the sum of residuals on March 3rd and May 31st.

County and consumer type (B - business or P - private)	Cumulative change	Initial consumption (kWh)	Consumption at the end of lockdown (kWh)	Minimal consumption (kWh)	Overall change in consumption
Harju, B	-1404.941	6502875	3720380	3720380	-17.42344%
Harju, P	284.4847	2738909	1731210	1641998	-11.07209%
Lääne-Viru, B	-1667.044	901326.1	509298.8	477400	-32.06526%
Lääne-Viru, P	-159.8362	352136.3	244950.8	217038.8	-6.608199%
Ida-Viru, B	-1618.195	825268.4	520175.1	439999.2	-19.66741%
Ida-Viru, P	323.4386	228732	176834.6	160236.2	-0.8954135%
Lääne, B	-762.1072	289733.9	154315.6	154315.6	-3.917585%
Lääne, P	-631.9569	340.8842	302.067	238.479	-14.11814%
Saare, B	-1420.324	318354.7	180623.8	180623.8	-12.15734%
Saare, P	-494.4902	200884.4	136918	126136.8	-14.30249%
Hiiu, B	-1176.159	92594.87	45405.06	38838.23	-20.17919%
Hiiu, P	-389.4888	62752.45	44822.46	40691.75	-3.809648%
Järva, B	-888.221	380355.9	240828.1	208519.7	-13.55068%
Järva, P	-220.9772	158897.6	113766.7	100884.7	-8.93412%
Rapla, B	-323.1153	461756.8	289249.6	289249.6	-4.073873%
Rapla, P	4.198068	253486.2	173099.6	152655.7	-4.566076%
Pärnu, B	-1033.742	939797.6	572947.4	572947.4	-13.07713%
Pärnu, P	-469.1432	485146.8	318695.5	292238	-17.46593%
Viljandi, B	-1128.327	489875.3	245984.3	241515.5	-15.88087%
Viljandi, P	-156.7105	231340	164330.9	148022.8	-8.450346%
Jõgeva, B	-630.2891	254292.8	154159	154159	-8.643266%
Jõgeva, P	51.49756	149948.7	111385.3	98440.82	-4.063171%
Tartu, B	-951.8952	1403610	820076.5	802839.3	-3.914909%
Tartu, P	109.2031	779470.5	540030.8	498393.2	-6.117414%
Valga, B	-156.2476	276872.5	169731.2	169071.9	6.045203%

Valga, P	224.8667	134539.7	100506	90976	-3.312133%
Põlva, B	-386.0736	193787.7	122032.2	122032.2	1.137237%
Põlva, P	674.5868	115088.1	89840.44	80626.96	8.451538%
Võru, B	34.42484	165507.3	226093	226093	1.196627%
Võru, P	556.1437	164815.8	127418.5	114484.4	1.889318%

Table 1. Summary of each county's results.

4.3.2 Summary of the results

The hardest hit counties were Harju, Ida-Viru, Lääne-Viru, and Saare, where the business consumers showed the heaviest decline in consumption. For Harju and Ida-Viru County, the private consumers had an increased demand, while Lääne-Viru and Saare County still had a negative change.

Hiiu County was similarly affected to Saare County, which coincides with heavier restrictions set on Western islands at the start of lockdown.

Counties with larger cities like Pärnu, Tartu, Viljandi, and Järva were also hit hard by the pandemic as seen by the business consumer consumption, but Tartu managed to recover faster from the decline than other counties. Tartu County private consumers also showed an increased demand overall.

Southern counties are not as dense in population and do not have large industrial consumers to be hit as hard as Northern counties were, therefore, their business consumers showed smaller declines, if not even an increase in consumption throughout the months of March to May. Private consumers showed a much larger increase in consumption in Southern counties than in Northern counties as well, which might be because the Southern counties likely have more private consumers.

5 Analysis

In this part, the results are analysed and compared with statistical data from Ministry of Finance and Statistics Estonia. Assessments are made on whether the government restrictions were efficient or too harsh for any separate county

5.1 Comparison with data from Statistics Estonia

The monthly turnover of enterprises chart from Statistics Estonia in year 2020 shows a large loss between March and April of about -17%, with a small recovery done in April. During May, the turnover increases substantially, but does not reach the levels of pre-pandemic, stagnating for the duration of June and dropping slightly again in July. [21]

When comparing the years 2020 and 2019, Statistics Estonia shows a -22.6% decrease for the month of April. The year 2019 had a small increase during March and April, and a dip in May. The energy consumption in Estonia followed a similar trend by dropping around 16% during April and gradually recovering from there, with small jumps in May. It is possible that the small jumps in May were instead due to 2019's small dip in turnover, and the actual consumption had a smaller and smoother increase instead.

Furthermore, to combat revenue losses, several companies also had to lay off their staff or close their doors entirely, the most severely affected being accommodation and food service industries.[22] This could have also led to an increase in consumption for private consumers, as they would have stayed at home for longer. However, the government put aside relief efforts for most affected enterprises for the lockdown period and larger layoffs happened instead during June-July, when the relief benefits likely would have been ended.[23]

5.2 Comparison with data from Ministry of Finance

The statistics from Ministry of Finance also showed a large decrease in the monthly revenue change in March and April of 2020, with a recovery in May, where March had a -18.5% decrease, April continuing the descent to a -20.4%. May increased to a -7.4%.[24]

The economic sentiment indicator[25] also showed a large drop in March and for the duration of April and May. Estonian Institute of Economic Research reported several problems the pandemic has had on enterprises, with 68% of enterprises reporting a lowered demand in production, 42% reporting a partial lack of employees (due to illnesses or quarantines), 41% finding it necessary to send employees on paid leave, and 25% of enterprises deeming it necessary to make employees redundant for the month of March.[26], [27]

This similarly correlates with the patterns for consumption change during lockdown, as lower demand for production also directly affects the need for energy consumption, and lack of employees both lowering to a smaller extent the business consumer energy consumption, while also increasing the private consumer consumption.

Furthermore, the Estonian Institute of Economic Research shows how the most affected sectors in businesses were food services and accommodation, with industries not much less affected. This correlates with the data in the county consumption, where the hardest hit counties for business consumers were those with largest cities in Estonia, industrial counties, or counties with strong tourism.

5.3 Patterns in economic losses and energy consumption

The data from Statistics Estonia and Ministry of Finance both follow a similar pattern to the general decline in energy consumption calculated by the regression model. Moreover, the data also suggests that counties with larger industries or higher density in population were hit harder due to problems caused by the pandemic, leading to a harsher drop in energy consumption.

Counties with a larger share of private consumers however were not hit as hard, or maybe even reported an increase in energy consumption, as seen in many Southern Counties, largely due to the lockdown and stay-at-home orders, or layoffs from companies. Instead, the increased consumption from private consumers caused the weekly cycles for private consumers to enlarge.

5.4 Analysis of county results and measures taken

Hiiu and Saare County are not very large when compared to Harju, Ida-Viru or Lääne-Viru counties, however they reported similar drops in proportion for business consumers. However, while Harju and Ida-Viru County showed an increase in private consumer consumption, the two islands still reported a decrease. This might be due to the additional measurements taken to combat the initial spread of the COVID-19 virus in Saaremaa and other Western islands.

While it is difficult to gauge whether the government took adequate measures to combat the spread of the virus or not, it is possible to see through energy consumption which counties suffered the worst. It is obvious for larger industrial counties to take the largest hits, so for smaller counties like Hiiu and Saare to report similar numbers could have been too harsh on business consumers on the islands, especially if the economic losses follow a similar trend for the counties as well.

When the Western islands went under additional restrictions to combat the spread of the virus, this further lowered the energy consumption. While some Southern counties also reported outbreaks, Saare County was the most affected in spread initially, causing people to stay at home even more than in other counties.[4] This with additional restrictions could have led to the difference in private and business consumer declines in consumption, whereas the Southern counties reported a growth.

Figure 18 shows the overall change in consumption from Table 1 for business and private consumers in each county. The most affected county by private consumers was Pärnu, with Saare and Lääne showing similar numbers. The most affected county by business consumers was Lääne-Viru, but Harju, Hiiu, and Ida-Viru also had close numbers. Smaller counties in population density or industries might show drastic changes because of weaker data, such as Lääne County, where the large change might be due to some companies starting or ending work.

Similarly, Southern counties and counties with low density might also show larger numbers in growth or smaller declines. Many have their private residences in counties with sparse population and might have travelled there to stay distant from the population when lockdown was issued. This could have been one of the reasons why these counties were less affected by the pandemic.

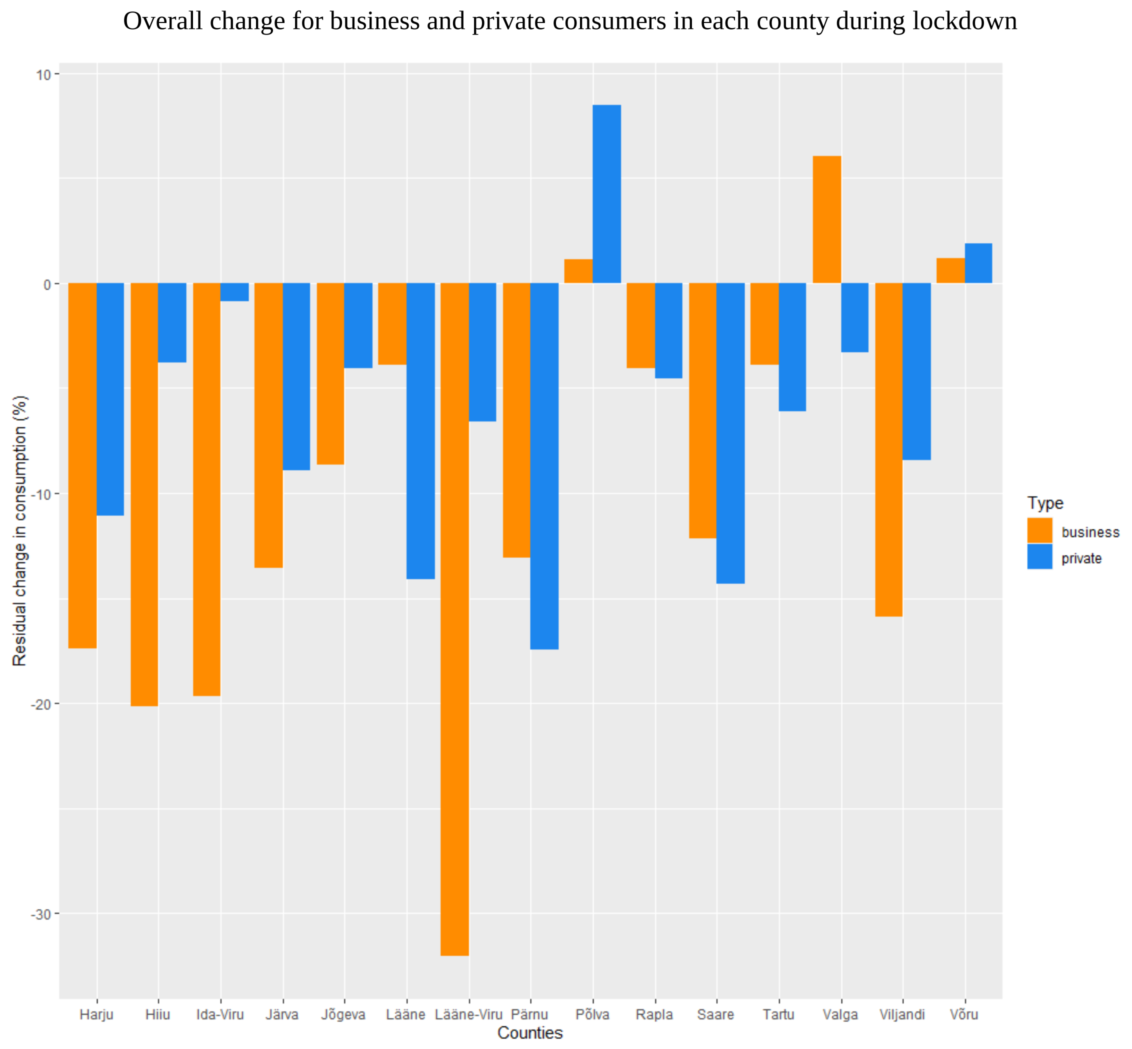

Figure 18. Business and private consumers are plotted together for comparison of how the pandemic and lockdown affected each county throughout the lockdown.

Therefore, it is difficult to guess whether the outcome for several counties would have been better with laxer restrictions, as it could have led to worse infection rates and that in return could have led to a worse decline in consumption with private consumers falling more ill and business consumers reporting even lower demands. However, densely populated counties and industrial counties were affected more by the measures taken than sparsely populated counties with a larger private consumer share, which could be something to be considered in future when modelling energy demand during health crises.

6 Further development and conclusion

6.1 Further development

There are several areas on which this thesis can be improved upon, as there were several problems that had to be corrected and processed.

For example, the weather and consumption measurements at times showed errors. More accurate measuring leads to more accurate calculations, which lead to more precise models. Currently, the data obtained was mostly from public domain, so someone with private measurements can ensure in the validity and correctness of the data at hand. Companies can have their own measurements taken for their own models. Also, the regression model can be improved upon with the usage of solar battery output measurements, which can be used to replace the calculations for light index.

Secondly, the model used in the thesis is a basic linear regression model, which is not as advanced as current models used in modelling of energy demand. Some work has already been done to develop elaborate and complex models that account for weather input and consider pandemic situations, but for the purposes of this thesis, no such model was developed as the goal was to determine the impact of pandemic on energy modelling.

Thirdly, the code in R can be heavily improved upon by programmers who are more proficient in the language than the author. Instead of every county and consumer type having explicit calculations, it can be turned into a dynamic function for a concise usage. Better knowledge of existing libraries can also optimise the speed of current processes and calculations by replacing more cumbersome formulas with commands from some library, if there are any. In addition, the overall change data in Tabel 1 can be improved upon with more precise calculations.

Finally, the existing results can be further analysed by experts from different fields with their own, more specialised and private data and statistics. This work was not done for any company, so the general analysis is broader and less specific for any company.

6.2 Conclusion

- Large industrial counties like Ida-Viru and Lääne-Viru, and densely populated counties like Harju and Tartu showed the largest reductions in energy consumption for business consumers.

- Tartu also had a swift recovery when compared to other larger counties.

- Southern counties and sparsely populated counties were impacted less by the lockdown, with Põlva, Valga, and Võru even reporting general increases in energy consumption.

- The Western islands Hiiu and Saare were impacted severely to the same levels of Harju and Lääne-Viru, likely due to the additional measures taken to combat the spread of COVID-19 during the outbreaks.

- The overall decline in consumption as aggregate of all county business consumers was -15% during March, lowering even further during April and showing a small recovery during May. June and July continued to gradually recover from the initial drop but compared to 2019 still had around 10% lower consumption.

- The decline in energy consumption follows a similar pattern to economic losses observed in Estonia, showing a significant drop in March, a recovery in May and a continuous recovery over summer.

- The measures taken during the pandemic show how sparsely populated counties or counties with a larger share of private consumers are impacted less than counties with strong business consumers or dense population, to the point where some even reported an increase in consumption.

- Stricter measures taken such as seen on Western islands can still cause a similar impact for smaller counties like seen with larger counties in population.

- Additional considerations must be made when modelling consumption for different sectors of industries depending on qualities of each region, as energy consumption depends on whether a county is more industrial or more involved with tourism, food or accommodation, population density, and statistical accuracy for those qualities.

- The developed regression model with elimination of weather impact can predict energy consumption reasonably well for up to five-six months with one month of training.
- Some counties react to state holidays differently, requiring additional consideration when calculating fits for the used regression model.

7 Summary

Modelling energy consumption accurately is vital for the health of present electricity grids, where models need to account for several different factors such as weather data. Errors in modelling can also lead to severe monetary losses for businesses or the general GDP of the country.

The pandemic and measures taken show how important it is to also predict human behaviour during varying degrees of restrictions – countries that had laxer restrictions showed a smaller decrease if not an increase in energy consumption, whereas harsher restrictions had larger declines in energy consumption.

In this thesis, a regression model developed by Kalda has been implemented in R to observe and compare Estonia's energy consumption data in 2019 and 2020 and determine the impact the pandemic has had on business and private consumers during lockdown periods.

Among the most affected counties in Estonia were Harju, Ida-Viru, Lääne-Viru, Saare, Tartu, and Hiiu. Saare and Hiiu County are not industrious but suffered from harsher restrictions to combat the outbreaks and therefore showed worse losses in consumption.

Harju, Ida-Viru, Lääne-Viru, and Tartu counties are all more densely populated and have larger businesses and industries, therefore the lockdown imposed the largest reductions in energy consumption for business consumers. However, Tartu County showed a quicker recovery from the rest.

Southern counties and sparsely populated counties with a larger share of private consumers were not affected as much, showing a smaller decline or an increase in private consumer consumption.

The overall decrease in energy consumption in Estonia was 15% in March and continued to drop below -15% during April, however started to recover in May. This coincides with economic reports and losses from Statistics Estonia and Ministry of Finance.

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