

¹ Highlights

² **The influence of resource use on yield versus sale price trade-off in**
³ **Australian vineyards**

⁴ Author

- ⁵ ● Comparative analysis of resource use, average sale price and quantity
⁶ in Australian winegrowing.
- ⁷ ● Regional comparison of outcomes and resource use in Australian wine-
⁸ growing regions.
- ⁹ ● Baseline models for comparing vineyards.
- ¹⁰ ● Analysis of national, decade long data source.

¹¹ The influence of resource use on yield versus sale price
¹² trade-off in Australian vineyards

¹³ Author^{1,1,1}

¹⁴ **Abstract**

When strategies for a sustainable winegrowing industry are assessed, there is a trade-off between balancing the amount of resources invested and the resultant yield and sale price of the produce. In this analysis we observe relationships between resource use, yield and sale price through the use of statistical models. The dataset used for this analysis includes data collected for the past 10 years from 1261 vineyards located over a diverse range of Australian winegrowing regions. Yield and sale price were evaluated with respect to the resource use factors water use and Green House Gas (GHG) emissions. The analysis confirmed a strong relationship between area and resource use, with the overall area of a vineyard and its access to resources greatly determining the upper limit of yield. However, area was also negatively related to the average sale price of grapes; we find that higher average sale prices were connected to high resource inputs per area, rather than to the overall expenditure of resources. Regional and temporal effects on vineyard yield and average sales price were also identified. Overall, the analysis highlighted the importance of considering a vineyard's business goal, region, external pressures and economies of scale, when considering whether to pursue higher yields or higher average sales prices.

¹⁵ **1. Introduction**

¹⁶ The global focus on sustainability in agronomic industries has changed
¹⁷ the way in which these enterprises do business. A dilemma exists across
¹⁸ agriculture through shared fundamental considerations of resource use such
¹⁹ as water and fuel, and the resultant yield and crop value that are produced
²⁰ (Hemming et al., 2020; Kawasaki and Uchida, 2016; ZHU et al., 2017). The
²¹ average price of grapes for wine production is driven through its integration
²² within the wine industry. An important connection between grapes and their
²³ price is the grape's perceived quality, which initially defines a wine's potential
²⁴ through the grape's chemical makeup (Black et al., 2015; Schreier and Jen-
²⁵ nings, 1979). Grapes of higher perceived quality or grapes from well known
²⁶ regions are likely to have higher prices (Wine Australia, 2021). Grape quality
²⁷ is connected to the market value of winegrapes, with Wine Australia explic-
²⁸ itly defining grape quality through the use of discrete price brackets in their
²⁹ annual reports (Winemakers' Federation of Australia, 2018). It is important
³⁰ to note that the generalisation made to reflect quality through using aver-
³¹ age price assumes a due diligence of those who purchase the grapes (Yegge,
³² 2001). The economic sustainability of a vineyard is tied to this market cul-
³³ ture, driven by the wine industry. The consideration of sustainability within
³⁴ viticulture is also subject to environmental and sociodemographic pressures
³⁵ (Santiago-Brown et al., 2015). In the Australian context, these pressures in-
³⁶ clude biosecurity, climate and international market changes (Canadell et al.,
³⁷ 2021; Longbottom and Petrie, 2015; Oliver et al., 2013).

³⁸ There is an extensive amount of research into the varied effects of factors
³⁹ on grape quality and yield (He et al., 2022; Laurent et al., 2022; Liakos et al.,

40 2018). Due to the lack of long-term and in-depth data there is a lack of
41 research on grape sale price and its driving factors. Furthermore, individual
42 factors are often studied in isolation with yield and sales price not appearing
43 together (Abbal et al., 2016). The lack of consolidated datasets restricts the
44 ability to gain statistical insights at large scales and across multiple regions.
45 As a result, broader studies are lacking (Keith Jones, 2002; Knight et al.,
46 2019). The dataset used for this analysis includes data spanning 10 years
47 from a multitude of vineyards located over a diverse range of Australian
48 winegrowing regions. We use this dataset to describe the relationship of
49 resources related to water and fuel use with the output yield and average sale
50 price of the resultant product, taking into account the size and location of the
51 vineyard. In a practical sense, this aim is a baseline for comparison: given
52 a vineyard within Australia, one could estimate the comparative efficiency
53 with regard to the trade-off between invested resources, yield and average
54 sale price. This is the first time that such a trade-off has been confirmed
55 explicitly across such varying regions, scales and climates in the Australian
56 winegrowing industry.

57 2. Methods

58 2.1. Data

59 Data used in these analyses were obtained from Sustainable Winegrow-
60 ing Australia and Wine Australia. Sustainable Winegrowing Australia is
61 Australia's national wine industry sustainability program, which aims to fa-
62 cilitate grape growers and winemakers in demonstrating and improving their
63 sustainability (SWA, 2022). Wine Australia is an Australian Government

Table 1: Summary of models; their predictors, covariates and variable interactions.

	Response	Predictors	Covariates	Interactions
Model 1	Yield	Water Used scope one Emissions	Area Harvested Year GI Region	N/A
Model 2	$\frac{\text{Yield}}{\text{Area Harvested}}$	Water Used scope one Emissions	Area Harvested Year GI Region	Area Harvested * scope one Emissions Area Harvested * Water Use Year * Region
Model 3	$\text{Yield} \times \text{Average Sale Price}$	Water Used Scope One Emissions	Area Harvested Year GI Region	N/A
Model 4	Average Sale Price	Water Used Scope One Emissions	Area Harvested Year GI Region	Area Harvested * Scope One Emissions Area Harvested * Water Use Year * Region
Model 5	Average Sale Price	Water Used Scope One Emissions	Year GI Region	Year * Region

64 statutory authority governed by the Wine Australia Act (Attorney-General's
65 Department, 2010). Data collected by Wine Australia are publicly available.
66 The response (predicted) variables in this analysis were yield, defined as the
67 total tonnes of grapes harvested, and average sale price of grapes in Aus-
68 tralian dollars per tonne. Both response variables were examined as totals
69 and also relative to area harvested (see Table 1). Values were compared in
70 this manner to observe how economies of scale affect the use of resources.

71 Data recorded by Sustainable Winegrowing Australia were entered manu-
72 ally by winegrowers voluntarily using a web based interface. For each model,
73 vineyards were only included if they recorded all the variables used for the
74 corresponding model (see Table 1). Each vineyard had at least recorded
75 region, harvest year, yield and area harvested. Other variables that were
76 used but not present for every single vineyard were average sale price, water
77 used and fuel used (diesel, petrol, biodiesel and LPG). To enable direct com-
78 parisons between fuels, fuel use was converted to tonnes of carbon dioxide
79 equivalent and collectively referenced to as emissions. All variables were con-
80 tinuous except for harvest year and region, which were categorical variables
81 (Table 1).

82 As data from Sustainable Wine Australia were voluntarily given, missing
83 values were improved using regional average prices from the Wine Australia
84 data. Data obtained from Wine Australia were collected via phone surveys
85 and included: total tonnes purchased, average price per tonne and yearly
86 change in price for region and grape varietal; with the data being publicly
87 available.

88 The dataset was split into two distinct subsets that could be used across

89 the different models. The first subset contained all vineyards and was used for
90 two models (Model 1 and Model 2, see Table 1). The second subset contained
91 vineyards which either recorded a value for average price of sale per tonne
92 through Sustainable Winegrowing Australia, or were within a region with an
93 average price of sale recorded by Wine Australia; this subset was used for
94 three further models (Models 3, 4 and 5, see Table 1). These subsets meant
95 that the data would be limited to samples which had recorded values for the
96 response variables (see Table 1), as every sample/vineyard had a recorded
97 value for yield but not average price of sale per tonne.

98 The first subset of data (used for Model 1 and Model 2, see Table 1)
99 contained 5298 samples spanning the period from 2012 to 2022, covering 55
100 GI Regions and 1261 discrete vineyards.

101 The second subset of data (used for Model 3, Model 4 and Model 5,
102 see Table 1) contained 2878 samples spanning the period from 2015 to 2022,
103 covering 51 GI Regions and 944 separate vineyards. Average price of sale per
104 tonne was extracted from both Wine Australia (1842 values) and Sustainable
105 Winegrowing Australia (remaining 1036 values).

106 Additional variables were considered for analysis but were excluded due
107 to being either underreported or had insignificant contributions to model
108 accuracies. Variables explored but not used due to low reporting values
109 included fertiliser (kg), electricity (Kw/h), and scope two emissions (TCO²
110 equivalent). Variables considered but ultimately removed due to a lack of
111 significant contributions to models, included the use of renewable energy, use
112 of contractors, and pressures such as frost, fire and disease.

113 Data preprocessing was conducted prior to analysis using the Python

114 programming language (G. van Rossum, 1995). Preprocessing included the
115 conversion of fuel to scope one emissions and prior calculations for all con-
116 tinuous variables which included logarithmic transformations, centring and
117 scaling by standard deviation. We converted multiple emission sources into
118 scope one emissions using the equation given from the Australian National
119 Greenhouse Accounts Factors (AGDEE, 2021). The calculation conducted
120 using

$$tCO_2e = \frac{Q \times EC \times EF1 + EF3}{1000}, \quad (1)$$

121 where emissions was the product of the quantity of fuel in litres, Q ,
122 a prescribed Energy Content, EC , and emission factors (as given by the
123 Australian National Greenhouse Accounts factors) of scope one, $EF1$, and
124 scope three, $EF3$, to tonnes of Carbon Dioxide Emission equivalent, $tCO2e$
125 (Department of Climate Change, Energy, the Environment and Water, 2022).

126 Differences in vineyard locations were captured through the use of Geo-
127 graphical Indicator Regions defined by Wine Australia (Halliday, 2009; Oliver
128 et al., 2013; SOAR et al., 2008). Although vineyards generally differed in in-
129 come, there were pronounced differences between regions as shown in Figure
130 1. These differences were likely due to the site of a vineyard being important
131 as it predetermines several physical parameters such as climate, geology and
132 soil, making location a widely considered key determinant of grape yield and
133 average sale price (Abbal et al., 2016; Agosta et al., 2012; Fraga et al., 2017).
134 Each GI Region has its own unique mixture of climatic and geophysical
135 properties that describes a unique winegrowing region within Australia and
136 is a protected trademark under the Wine Australia act (Attorney-General's
137 Department, 2010). Both Wine Australia and Sustainable Winegrowing Aus-

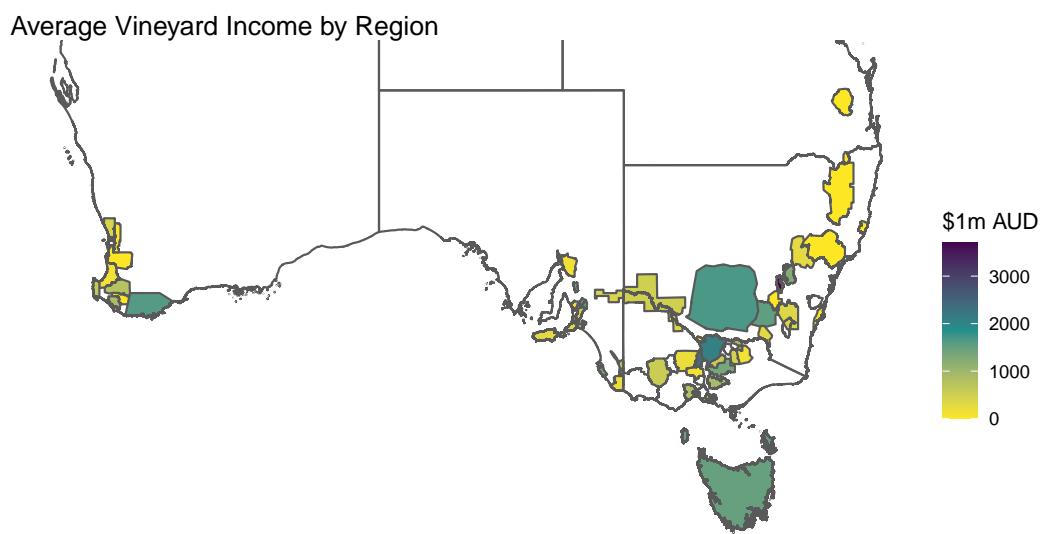


Figure 1: Map of each GI Regions' (outlined by Wine Australia) average income for a vineyard of that region (average grape sale price per tonne \times total tonnes yielded).

138 tralia used the same GI Region categorical variable format to describe loca-
139 tion.

140 The climatic properties of each GI Region were summarised by using pre-
141 defined classifications as per the Sustainable Winegrowing Australia (2021)
142 user manual. The user manual describes climates by rainfall and tempera-
143 ture, creating supersets of Regions of similar climatic properties. The cli-
144 matic groups were used to illustrate similarities and differences occurring in
145 areas larger than GI Regions.

146 *2.2. Analysis*

147 Pairwise Pearson Correlation Coefficients (PPCC) were calculated to as-
148 sess the potential existence of linear relationships between the input and
149 predicted variables. To determine if a coefficient was indicative of a strong
150 relationship, both the magnitude of the value and the associated confidence
151 intervals were evaluated. P-values reflected the significance of a given corre-
152 lation coefficient with statistical significance being declared when the corre-
153 sponding P-value was lower than 0.05. PPCC analyses were undertaken for
154 data on the original scale and for data as a logarithmic transform. Trans-
155 forming data prior to calculating the coefficients changes several things. The
156 logarithmic transform of the data alters the interpretation of the coefficients
157 to percentage change; a coefficient will be indicative of the change in per-
158 centage of one variable compared to the other, scaling by standard deviation
159 also changes this interpretation to be a percentage of that variables standard
160 deviation. When considering the logarithmically transformed variables, a co-
161 efficient of 1 would indicate that the change of one variable by one percentage
162 of its standard deviation would correlate to the other variable changing by

163 one percent of its own standard deviation. The importance of this is the
164 dimensionless nature of these relationships and that it can be translated di-
165 rectly to any vineyard's case that has a well known distribution.

166 Five general linear models (GLMs) were created (see Table 1). GLMs were
167 chosen as they offer the ability to produce statistical models that are explicit
168 in the relationships between predictors and response variables. General Lin-
169 ear Models also allowed the exploration of interactions between predictors
170 and allow for easily comparable differences in the influence and magnitude
171 of relationships. Model fit was measured in terms of R^2 and adjusted R^2
172 as well as F statistics, and t-tests were used to determine if predictors sig-
173 nificantly contributed to the models when accounting for other variables,
174 showing which specific years and areas contributed significantly. Both the
175 PPCC and GLM analyses were created using the R statistical programming
176 language (R Core Team, 2021) with the Caret package (Kuhn, 2008).

177 A variety of alternate methods were also explored, including splines, hi-
178 erarchical regression, general additive models, and generalised linear models.
179 These alternative approaches were not used as final models due to offering
180 little further insights or improvements in accuracy.

181 *2.3. Model Validation*

182 Models were validated using K-fold cross validation. This was performed
183 by removing a subset of data from the sample used to train models and then
184 predicting those variables to determine how sensitive the model is to changes
185 in the sample data. For this analysis, each model was validated using 10
186 folds, repeated 100 times.

Table 2: Summary statistics of each continuous variable.

Variable	Mean	Standard Deviation	Minimum	Maximum
Yield (tonnes)	7.76E+02	2.18E+03	1.00E+00	7.23E+04
Area Harvested (ha)	6.67E+01	1.34E+02	7.00E-02	2.44E+03
Water Used (ML)	7.47E+06	5.65E+08	1.00E+00	4.27E+10
Scope One Emissions (tCO_2e)	4.17E+04	8.57E+04	6.76E+00	2.11E+06
$\frac{\text{Yield (tonnes)}}{\text{Area harvested (ha)}}$	1.01E+01	8.13E+00	4.00E-02	8.63E+01
Average Sale Price (AUD/tonne)	1.48E+03	9.22E+02	1.60E+02	2.60E+04
$\frac{\text{Average Sale Price (AUD/tonne)}}{\text{Area Harvested (ha)}}$	1.35E+02	5.71E+02	1.75E-01	2.98E+04

¹⁸⁷ **3. Results**

¹⁸⁸ *3.1. Exploratory Analysis*

¹⁸⁹ Table 2 shows the summary statistics of each variable in its original units.

¹⁹⁰ The range of these values shows the level of difference between some vine-
¹⁹¹ yards, with operations differing by orders of magnitude in size, yield and
¹⁹² average price of sale (See Table 1).

¹⁹³ PPCCs values for the transformed, centred and scaled variables are shown

Table 3: Pairwise Pearson correlation coefficients for logarithmically transformed values.

	Yield	Area Harvested	Water Used	Scope One Emissions	Yield by Area	Average Price	Average Price by Area
Yield	1.00	0.88	0.82	0.76	0.96	-0.46	-0.88
Area Harvested	0.88	1.00	0.78	0.83	0.73	-0.19	-0.81
Water Used	0.82	0.78	1.00	0.67	0.76	-0.49	-0.82
Scope One Emissions	0.76	0.83	0.67	1.00	0.65	-0.16	-0.67
Yield by Area	0.96	0.73	0.76	0.65	1.00	-0.54	-0.84
Average Price	-0.46	-0.19	-0.49	-0.16	-0.54	1.00	0.72
Average Price by Area	-0.88	-0.81	-0.82	-0.67	-0.84	0.72	1.00

in Table 3. The process of centring and scaling variables changes them so that their mean is centred on 0 and all values are scaled to the variables standard deviation, such that 1 is equal to the variables standard deviation. All correlations were found to be statistically significant ($p < 2.200E-16$), and except for Average Sale Price all variables were positively correlated. With water use, area harvested and emissions being positively correlated to yield, it can be considered that more resources and area are likely to lead to greater yields. The negative correlations between Average Sale Price and Yield, Water Use, Area and Scope One Emissions each indicated that Area Harvested and Fuel Use separately were not the determining factor for average sale price. The negative correlations are associative, not causal relationships (i.e using more water does not cause lower sale prices).

3.2. General Linear Models

Each model had a high R^2 value, indicating that most of the variance within the data was described by the models (see Table 4) and statistical

Table 4: Summary of models; their performance, F-statistics and Residual error.

	R ²	Adjusted R ²	F-Statistic	P-Value	Residual Standard Error	Residual Sum of Squares	Residual Mean of Squares
Model 1	0.9072	0.9061	775.3	2.200e-16	0.3065	491.3	0.1
Model 2	0.8291	0.8141	55.07	2.200e-16	0.4312	905.03	0.19
Model 3	0.9753	0.9748	1885	2.200e-16	0.1589	71.11	0.03
Model 4	0.9091	0.9006	106.1	2.200e-16	0.3153	261.41	0.10
Model 5	0.9089	0.9004	107.2	2.200e-16	0.3155	262.04	0.10

209 significance of F-tests ($p < 2.200E-16$). Aside from 3 variables, all regression
 210 parameters were also statistically significant from zero, F-tests across each
 211 model's variables were ($p < 0.05$). The three exceptions were: scope one
 212 emissions in Model 3 ($p=0.22$) and Model 4 ($p=0.0.39$), and the interaction
 213 between area harvested and water used in model 2 ($p=0.22$). Note that scope
 214 one emissions was included in all models to directly compare the response
 215 variables as ratios of vineyard size to raw values and because it was strongly
 216 correlated to the response variable in every model (except model 5) especially
 217 for Models 1 and 4 (Table 3).

218 Coefficients related to continuous variables are summarised in Table 5.
 219 In Model 1 all coefficients except for the intercept significantly contributed
 220 to the model ($p < 0.05$), and in Model 2 all coefficients were statistically
 221 significant ($p < 0.05$). However, scope one emissions did not significantly
 222 contribute to models 3, 4 and 5. Model 4 only had statistically significant
 223 contributions from the intercept and water use. Although the coefficient for
 224 water use was statistically significant for each model, it did not have the

Table 5: Summary of each Model's coefficients for continuous variables

		Intercept	Area Harvested	Water Used	Scope One Emissions	Area Harvested *	Area Harvested *
					Scope One Emissions	Water Used	
Model 1	Coefficient	-3.32E-02	7.42E-01	8.66E-02	6.73E-02		
	Std Error	1.96E-02	1.00E-02	8.90E-03	8.00E-03		
Model 2	Coefficient	1.70E-01	5.77E-01	1.08E-01	8.50E-02	-4.97E-02	-5.35E-02
	Std Error	5.91E-02	1.48E-02	1.31E-02	1.17E-02	8.10E-03	8.40E-03
Model 3	Coefficient	1.81E-02	9.71E-01	-2.31E-02	-7.00E-03		
	Std Error	1.30E-02	7.20E-03	6.90E-03	5.70E-03		
Model 4	Coefficient	1.45E-01	2.40E-03	-4.66E-02	-1.70E-02	1.15E-02	1.40E-03
	Std Error	5.28E-02	1.50E-02	1.43E-02	1.18E-02	7.90E-03	8.30E-03
Model 5	Coefficient	1.52E-01		-4.04E-02	-1.71E-02		
	Std Error	5.27E-02		1.13E-02	9.70E-03		

225 highest value; instead, area harvested, being an order of magnitude greater,
 226 dominated the models. Model 5 achieved a similar R^2 to Model 4 without
 227 area harvested, having stronger influences from water use and scope one
 228 emissions.

229 The regression coefficients for the Year variable of each model is depicted
 230 in Figure 2. For each model, the first year for a model's was used as the
 231 baseline: 2012 for Models 1 and 2, and 2015 for Models 3, 4 and 5. Adelaide
 232 Hills is used as the regional baseline with the interaction between year and
 233 region using the first year and the Adelaide Hills as the baseline. Region and
 234 year contributed, in some but not all cases, more than the other variables.
 235 However, the coefficients varied substantially over the years, and were not
 236 significantly different from zero in some years. Models 4 and 5 are very similar
 237 in Figure 2, indicating that the exclusion of area does not greatly affect the

contribution from yearly influence. Models 4 and 5 have the most prominent trends, showing an increase in yearly effects over time, with Model 3 also increasing from 2016 to 2018, but plateauing afterwards. Model 1 and 2 do not show a clear trend, but do drop during 2017 and 2018 after increasing in the first 3 years.

Regional differences by temperature and rainfall are summarised in Figure 3. The most notable difference is between vineyards within 'Hot' and 'Very Dry' regions (warm inland regions), where high average sale prices are historically low, and yield is high. Water Use changes dramatically between these regions as well, with water being a driving force for yield but not necessarily average sale price. The warmer and drier regions tend to also have larger vineyards. These regional differences are further shown in Figure 4, as a ratio of vineyard; where there is a pronounced difference in 'Hot' and 'Very Dry' regions producing more per area with lower average sale prices per area than other regions.

Figure 4 further shows the emphasis that 'Hot' areas have on high yields, with low average sale price compared with other regions. Scaling average price and yield by area shows a strong negative trend, trading quantity for higher sales prices.

Table 3.2 shows the validation results of each of the models. The R^2 measures of fit show similar results to the initial models, with a slight decrease as expected, indicating that the models are robust and consistent.

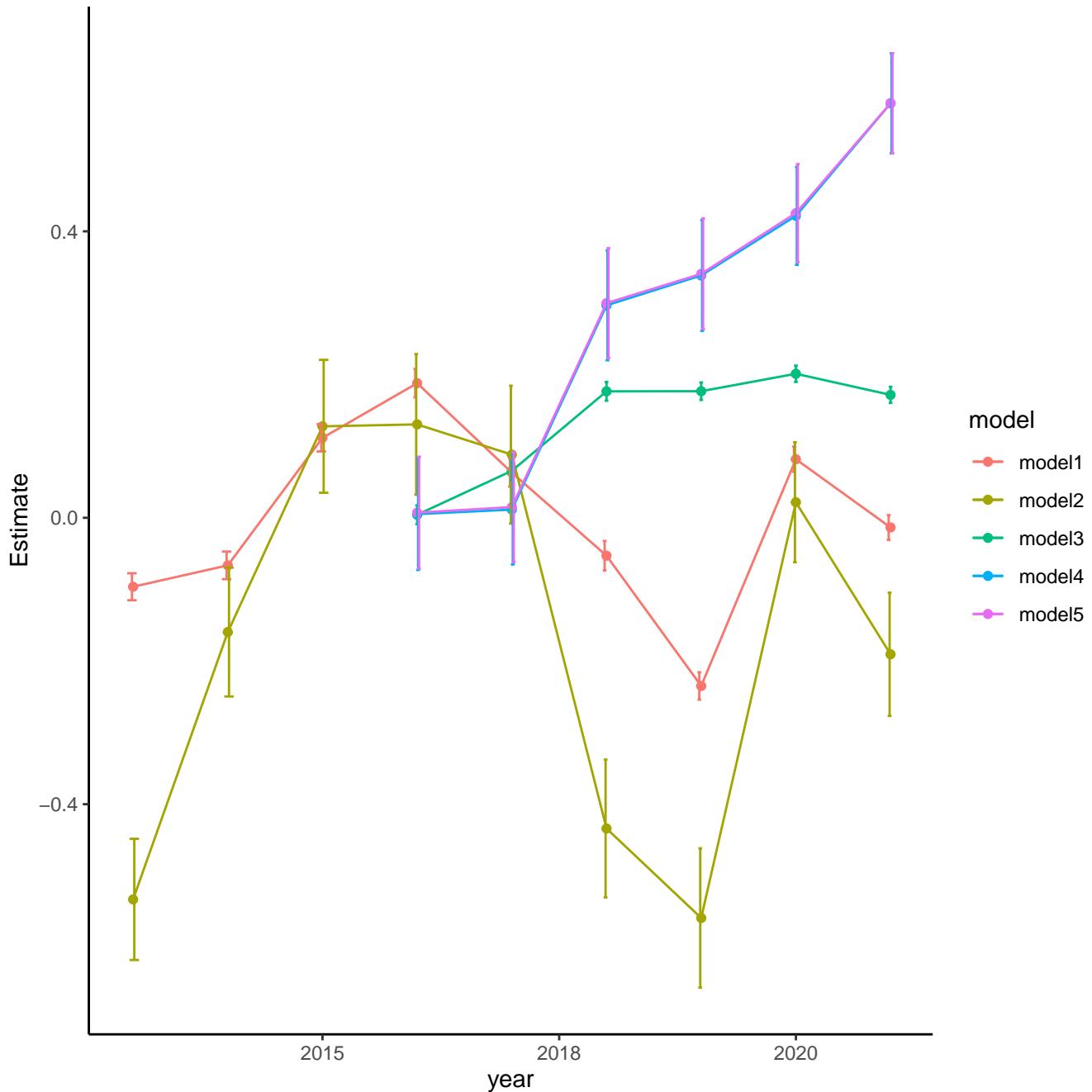


Figure 2: Model Coefficient values for Year, with standard error bars.

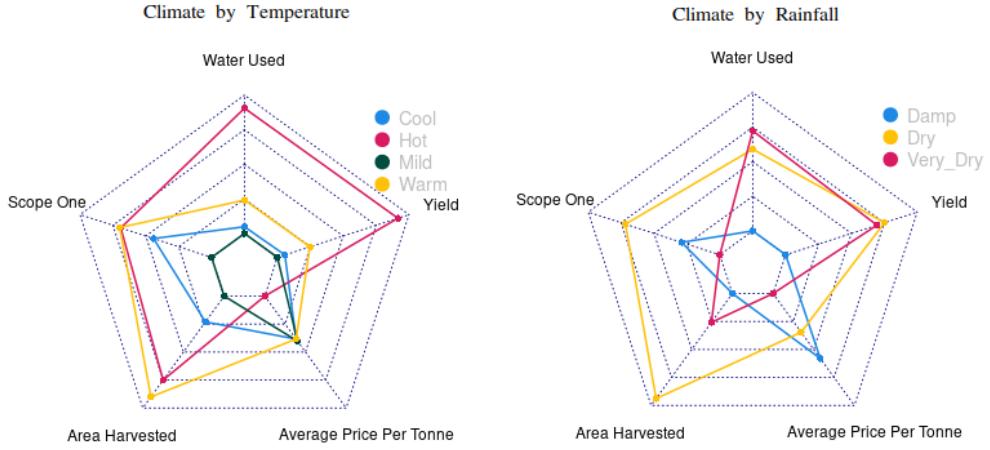


Figure 3: Radar plot of climatic profile's resource use, yield and average sale price. The left reflects vineyards in different climatic temperatures. The right reflects vineyards in different rainfall climates.

Table 6: Model validation using k-fold cross validation, for 10 folds repeated 100 times.

	Residual Mean Squared Error	R2	Mean Average Error
Model 1	.309	.905	.2165
Model 2	.457	.7921	.313
Model 3	.165	.972	.101
Model 4	.348	.878	.182
Model 5	.348	.878	.183

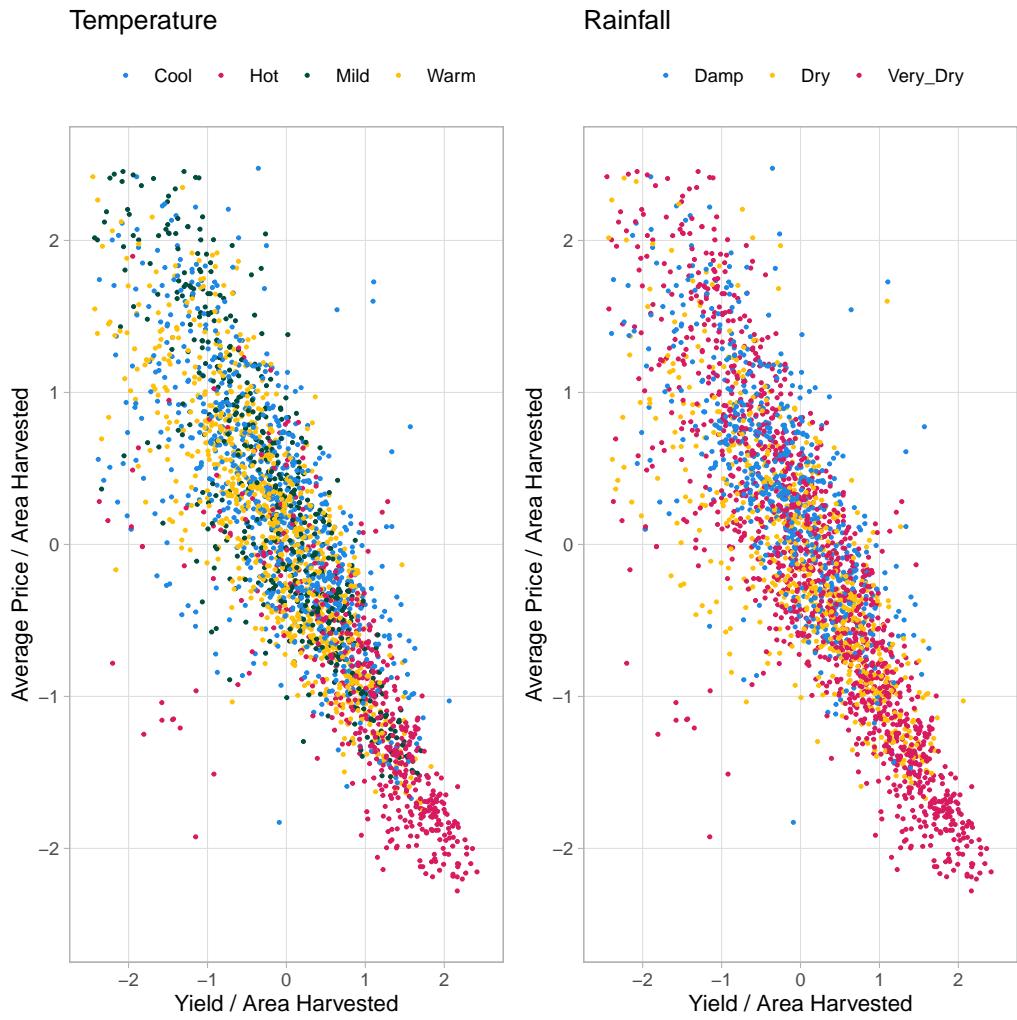


Figure 4: Scatter plot of vineyard yield against the average sale price as ratios to area harvested. The axes are in standard deviations with points coloured by climate.

260 **4. Discussion**

261 There was an expected strong relationship between size and resource use,
262 with the overall area of a vineyard and its access to resources greatly deter-
263 mining the upper limit of potential yield. However, size was also inversely
264 related to the potential average sale price. Higher average sales prices were
265 also related to high resource inputs per area instead of the overall expendi-
266 ture of resources. Vineyard yields and sales price changed greatly by region
267 and year. Even given regional and yearly changes, there was a strong con-
268 nection between smaller vineyards and higher sales prices. This could have
269 been due to more attention available when managing smaller properties.

270 The lack of significance of scope one emissions and its contribution to
271 models, given its F-statistics, could be indicative that other vineyard activi-
272 ties requiring fuel are not leading factors for a vineyards average sale price.
273 The relationship between yield, value and area was not simply about effi-
274 ciently producing the most grapes. It is possible that the relationship of
275 scope one emissions between yield and sale price was closely tied to a vine-
276 yard's area due to requiring more fuel to address more issues over greater
277 distances. It is difficult to discern the connection of scope one emissions
278 directly, as fuel can be used for a broad category of activities.

279 There are important considerations unique to winegrowing compared to
280 other agricultural industries. The vertical integration of winegrowing within
281 the wine industry ties winegrowers to secondary and tertiary industries, such
282 as wine production, packaging, transport and sales. This results in unique
283 issues and considerations for each vineyard, where on-the-ground decisions
284 are influenced by other wine industry's choices, such as the use of sustainable

285 practices in vineyards as a requirement for sale in overseas markets; notably
286 these interactions can be further complicated by some winegrowers being
287 completely integrated into a wine company, while others are not (Knight
288 et al., 2019). Incorporating decisions into the model could help describe
289 the contributing factors to regional differences beyond resource consumption,
290 motivating the call for more granular data and more sophisticated modelling.

291 There are many on-the-ground decisions that influence both sales price
292 and yield. The decision to prioritise average sale price over quantity, is gov-
293 erned by complex physical and social forces, for example international market
294 demands, disease pressures and natural disasters (Abad et al., 2021; Cortez
295 et al., 2009; Hall et al., 2011; I. Goodwin, et al., 2009; Kasimati et al., 2022;
296 Oliver et al., 2013; Srivastava and Sadistap, 2018), with many of these oc-
297 currences being highlighted throughout the reports from Wine Australia over
298 the past decade (Wine Australia, 2019, 2021, 2022; Winemakers' Federation
299 of Australia, 2013, 2014, 2015, 2016, 2017, 2018). However, the changes in
300 the coefficients (see Figure 2) are not reflective of many known occurrences,
301 such as the 2020 bush fires, which had higher values for coefficients than prior
302 years; During the 2020 bush fires 40,000 tonnes of grapes were lost across 18
303 different wine regions due to bush fires and smoke taint. In comparison to
304 countrywide pressures such as drought, this damage made up only 3% of the
305 total amount of grapes for that year; although acknowledged as a consider-
306 able loss on an individual basis, it was deemed to be only a minor national
307 concern by Wine Australia when compared to other environmental pressures
308 such as drought (Wine Australia, 2020)

309 Climatic pressures are an important consideration for growers, especially

310 those in warmer and drier regions. The Wine Australia reports also show
311 that warm inland regions have seen a decline in profit over the past decade,
312 whereas regions with lower average sales prices did not (Wine Australia,
313 2019, 2020, 2021; Winemakers' Federation of Australia, 2013, 2014, 2015,
314 2016, 2017, 2018). Vineyards in warm inland regions also tend to be larger,
315 making up for lower sale prices with larger yields. Considering the negative
316 correlation of average price to area, for this strategy to work, economies
317 of scale become an important factor. Given the large quantities of grapes
318 that can be produced by some vineyards, even at low margins there is the
319 potential to be profitable. However, the increasing climatic pressures mixed
320 with the requirement for larger volumes of water, make the sustainability
321 of some vineyards come into question. Furthermore, intensive farming in
322 general is known to jeopardise the sustainability of an operation through the
323 degradation of soil and waterways (Capello et al., 2019; Lin, 2012; Pisciotta
324 et al., 2015). There are established methods that can help to mitigate these
325 effects, such as the use of cover crops, midrow crop rotation and efficient
326 irrigation.

327 Some regions appeared to produce grapes of lower average sale price at
328 scale whilst others achieved higher priced grapes in lower volumes. This
329 empirical finding is consistent with Wine Australia's annual reports, which
330 shows that some GI regions are known for producing large amounts of lower
331 grade (low value per tonne) grapes (Wine Australia, 2022; Winemakers' Fed-
332 eration of Australia, 2017). Comparatively, other regions only produce grapes
333 of higher sales price but in smaller quantities. The difference in pricing per
334 tonne between the lowest and highest regional average sales prices was almost

335 a hundred times, showing that region had a profound influence. Some regions
336 also had a mixture of high and low average sales price and yield showing re-
337 gional variability in pricing which may be explained by varieties produced. A
338 further possibility is the existence of regional upper limits on potential sales
339 price, or that there are diminishing returns in some regions when pursuing
340 higher sales prices or quantity; however these types of relationships may be
341 obfuscated by knowledgeable winegrowers who avoid such pitfalls.

342 Due to regional differences, different strategies are employed, such as
343 some regions targeting mass production over higher sales price. This is most
344 notable when grouping regions by climate, especially when considering GI
345 Regions in the 'Hot Very Dry' climate (see Figure 4). Figure 3 also shows that
346 comparatively 'Warm' and 'Dry' Regions manage their resources incredibly
347 efficiently having generally larger areas using similar resources to those in
348 'Cool' regions but having areas comparable to regions in 'Hot' climates. The
349 coefficients for Model 4 also show a greater benefit of resource use per area
350 when producing grapes at higher average sale prices, showing higher resource
351 use per area reflective of higher average sales price (see Table 2). Although
352 not chosen over GI region, climate was considered to be a large determinant
353 of the ability to produce larger quantities of grapes, as well as a determinant
354 in grape sale price (Agosta et al., 2012). The more granular GI Region likely
355 explained a broader mix of geographical phenomenon, such as soil, geology
356 and access to water resources (Abbal et al., 2016; Carmona et al., 2011). The
357 interaction between year and GI Region likely accounted for events such as
358 bushfires, which would be impactful, but only at a local level, both in time
359 and space.

360 We identified two main limitations to our linear modelling. First, model
361 1 and 2 over-predicting yield may have been due to preventative measures
362 brought on by regional pressures such as fire, frost and disease. More fuel
363 and water was likely used to prevent these issues from spreading within a
364 region, thus disproportionately affecting some vineyards compared to oth-
365 ers locally. This type of maintenance is not well captured in the models,
366 especially when considering that some regions, especially those in warmer
367 areas, are not as prone to disease as cooler climates and could potentially
368 have lower fuel and water use per hectare. This could create a discrepancy in
369 vineyards that utilised preventative measures in wetter regions, as opposed
370 to those that did not, thus expending less fuel and energy but risking disease.
371 When reviewing the differences between regions, it is important to consider
372 that vineyards in 'Hot Very Dry' areas can be hundreds of times the size of
373 those in other regions. This limitation could be overcome by incorporating
374 the profitability of vineyards, comparing the financial success of working at
375 different operational scales.

376 The second limitations was the lack of further explanatory variables to
377 help link models to causal affects. Variables such as the utilisation of renew-
378 able energy, contractors, and the occurrence of disease, fire and frost were
379 originally explored to capture the discrepancies between similar vineyards
380 that produced different yields and crop values. However, none of these vari-
381 ables was significantly correlated with the response variables, and did not
382 add to model accuracy, even when considered as interactions. Allowance
383 for nonlinear relationships, specifically through splines, resulted in more nor-
384 mally distributed residuals but at a drastically reduced overall accuracy when

385 comparing R^2 and Residual Square Error. Attempts to fully explain small
386 variations was always overshadowed by the dramatic differences in regional
387 trends. Having more data for each region would also be beneficial, allowing
388 greater comparison between regions.

389 The use of other models such as random forests and decision trees along-
390 side more variables and data may help to uncover the reasons for under or
391 overestimation. These differences could be caused by the use of alternative
392 sustainable practices in the field. Moreover, while there is evidence to suggest
393 that environmentally sustainable practices can reduce costs, and increase effi-
394 ciency whilst improving the quality of grapes; more research is needed to link
395 these benefits across different regions and climates (Baiano, 2021; Mariani
396 and Vastola, 2015; Montalvo-Falcón et al., 2023).

397 5. Conclusion

398 This study delved into the relationships between resource use, grape sales
399 price and yield. The findings underscore the multifaceted nature of vineyard
400 management, where the interplay of size, resource allocation, climate, and
401 regional influences collectively shape both the expected sale price and the
402 quantity of grape yields. Average sales price of grapes was not solely tied
403 to the overall expenditure of resources, but rather to the efficient allocation
404 of resources per area. This emphasises that factors beyond sheer scale con-
405 tribute significantly to the final sale price of grapes produced. Moreover, re-
406 gional and yearly variations exhibited substantial effects on vineyard outputs,
407 impacting both sales price and quantity. The connection observed between
408 smaller vineyards and higher grape sale price suggests that the management

⁴⁰⁹ of smaller properties might be more efficient and profitable.

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Table A.7: P-values for the non-transformed water used variable's Pearson correlation coefficients.

Variable	Water Used
Yield	7.538E-01
Area	6.981E-01
Scope One Emissions	8.883E-01
$\frac{\text{Yield}}{\text{Area}}$	6.836E-01
Average Price Per Tonne	5.600E-02
$\frac{\text{Average Price per tonne}}{\text{Area}}$	1.522E-01

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⁵⁵⁰ Appendix A. Appendix

Model 1 – Normal QQ

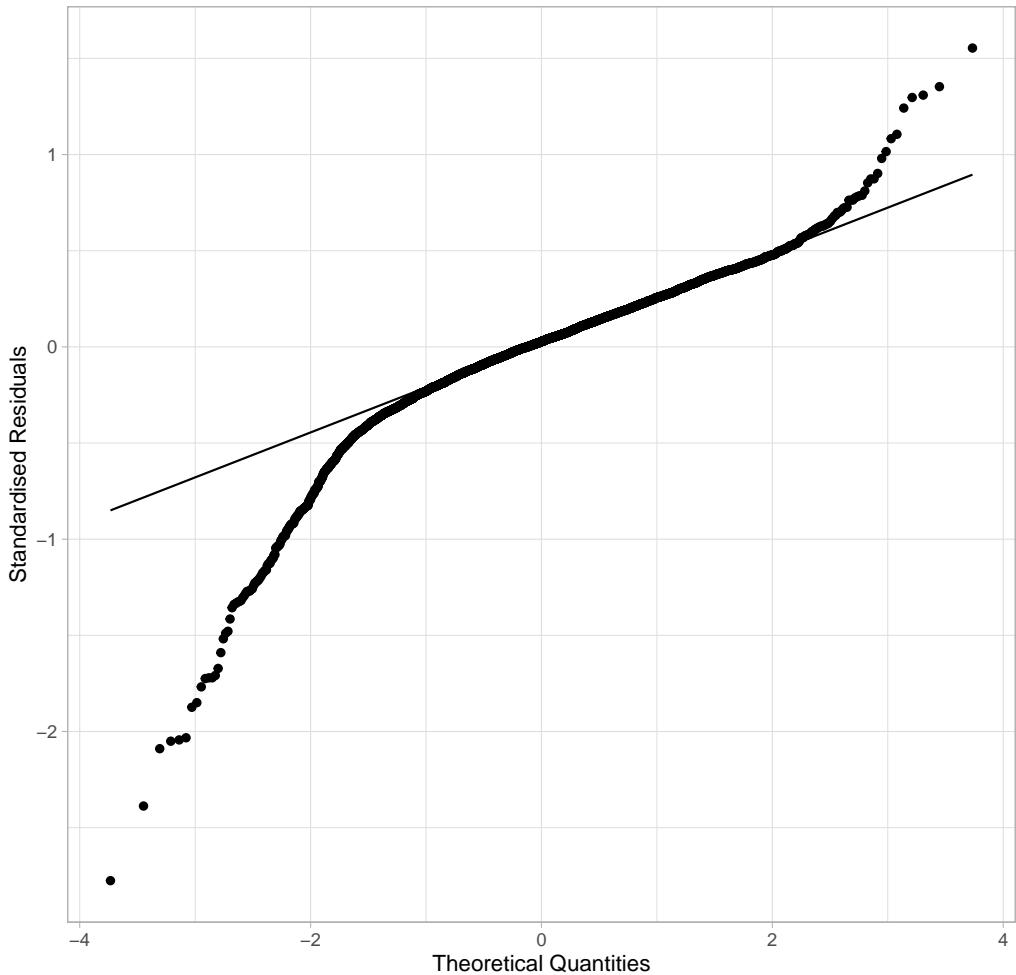


Figure A.5: QQ-plot of Model 1.

Model 1 – Residuals vs fitted

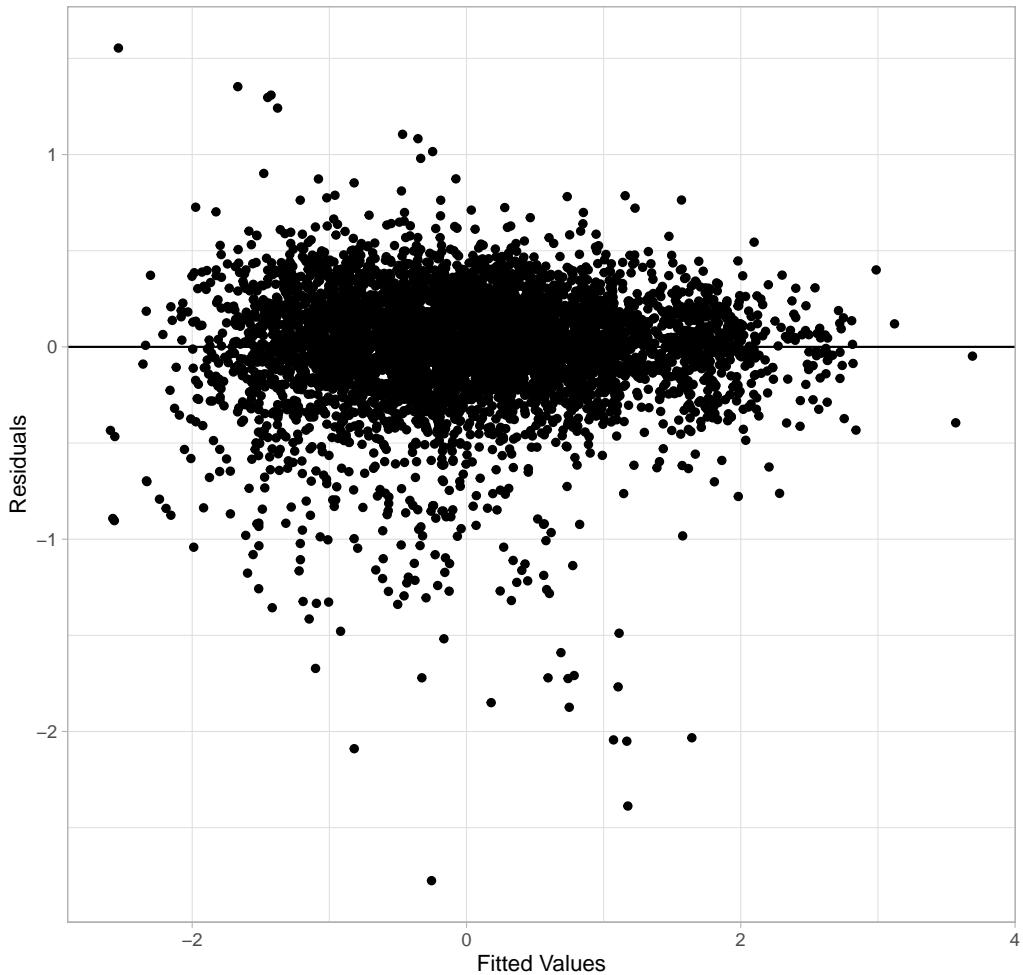


Figure A.6: Residuals vs fitted values for Model 1.

Model 2 – Normal QQ

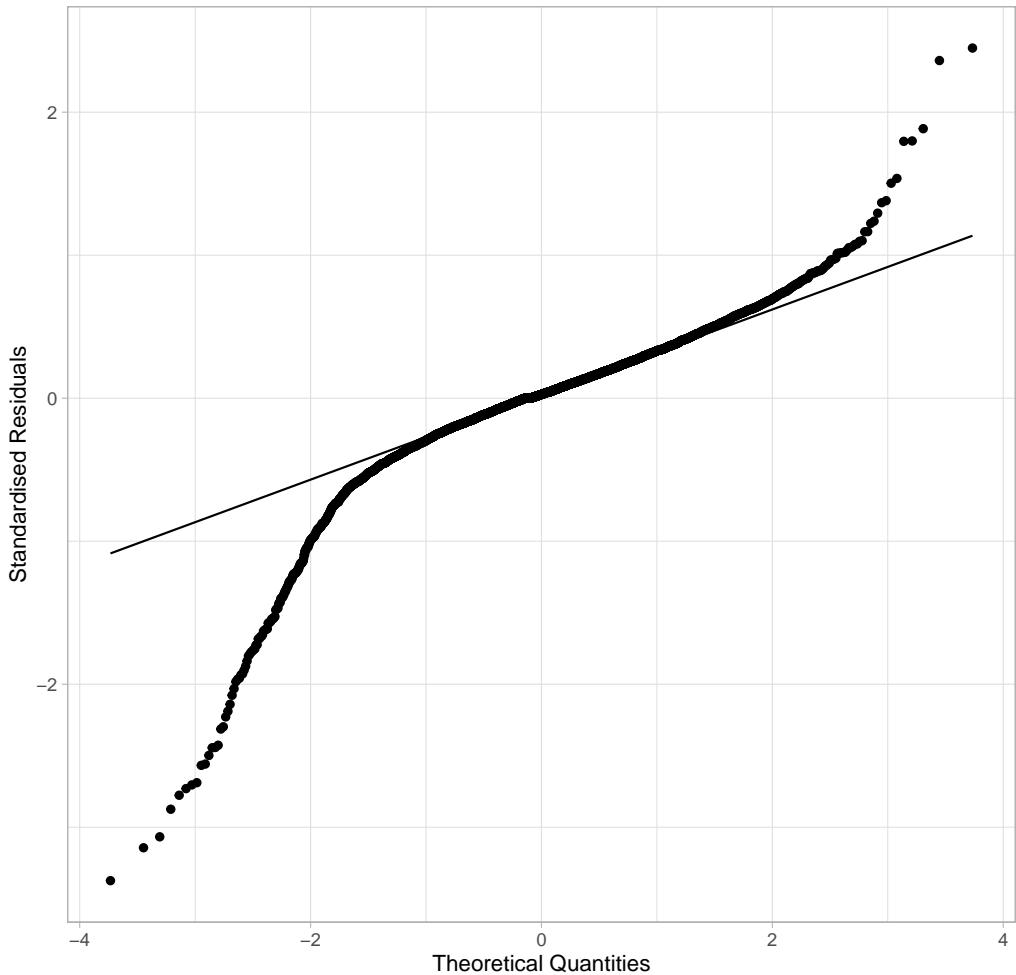


Figure A.7: QQ-plot of Model 2.

Model 2 – Residuals vs fitted

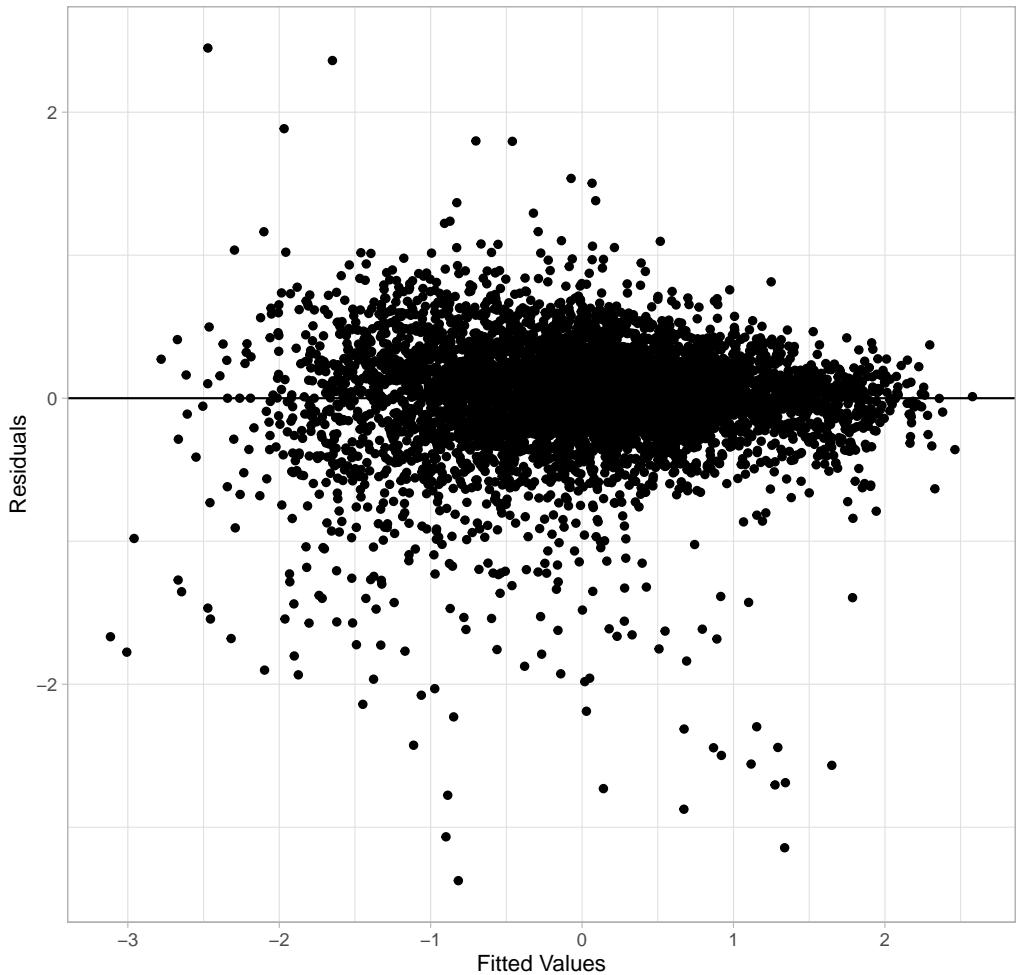


Figure A.8: Residuals vs fitted values for Model 2.

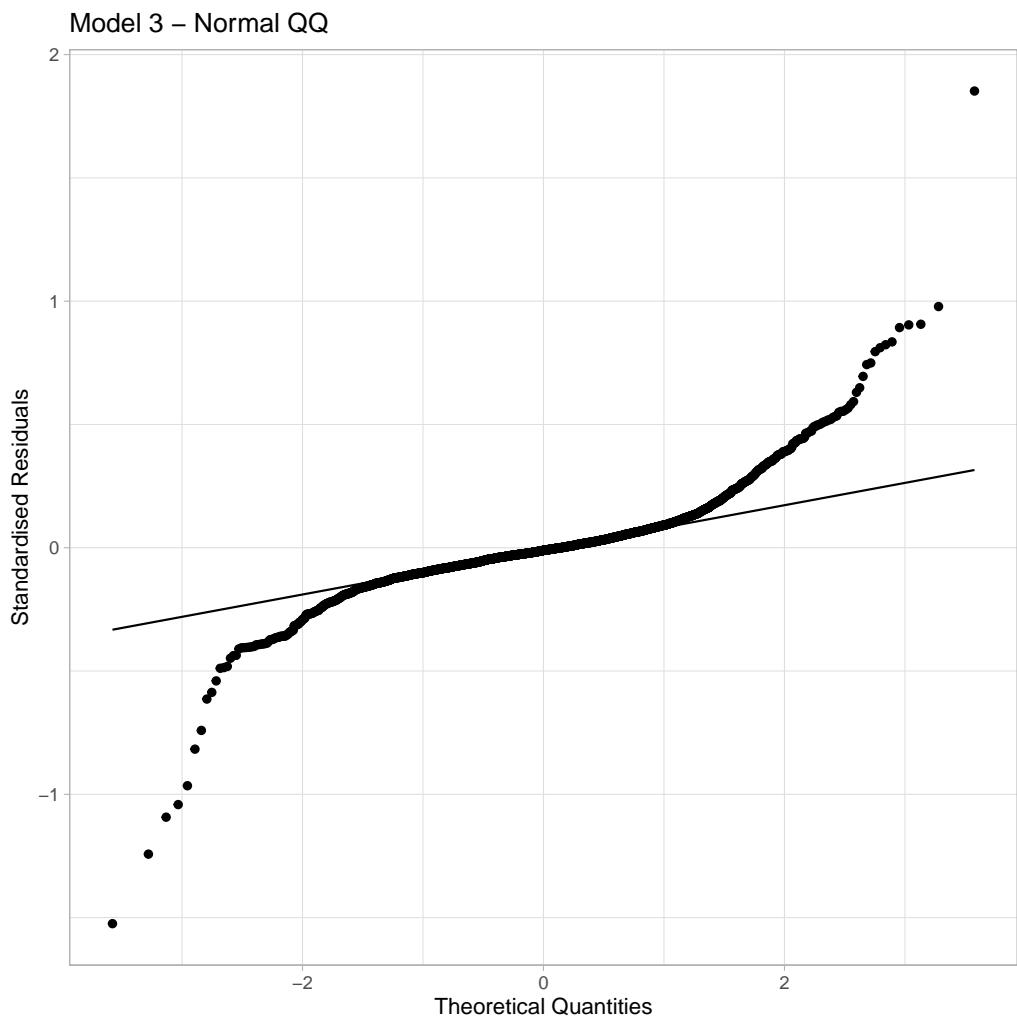


Figure A.9: QQ-plot of Model 3.

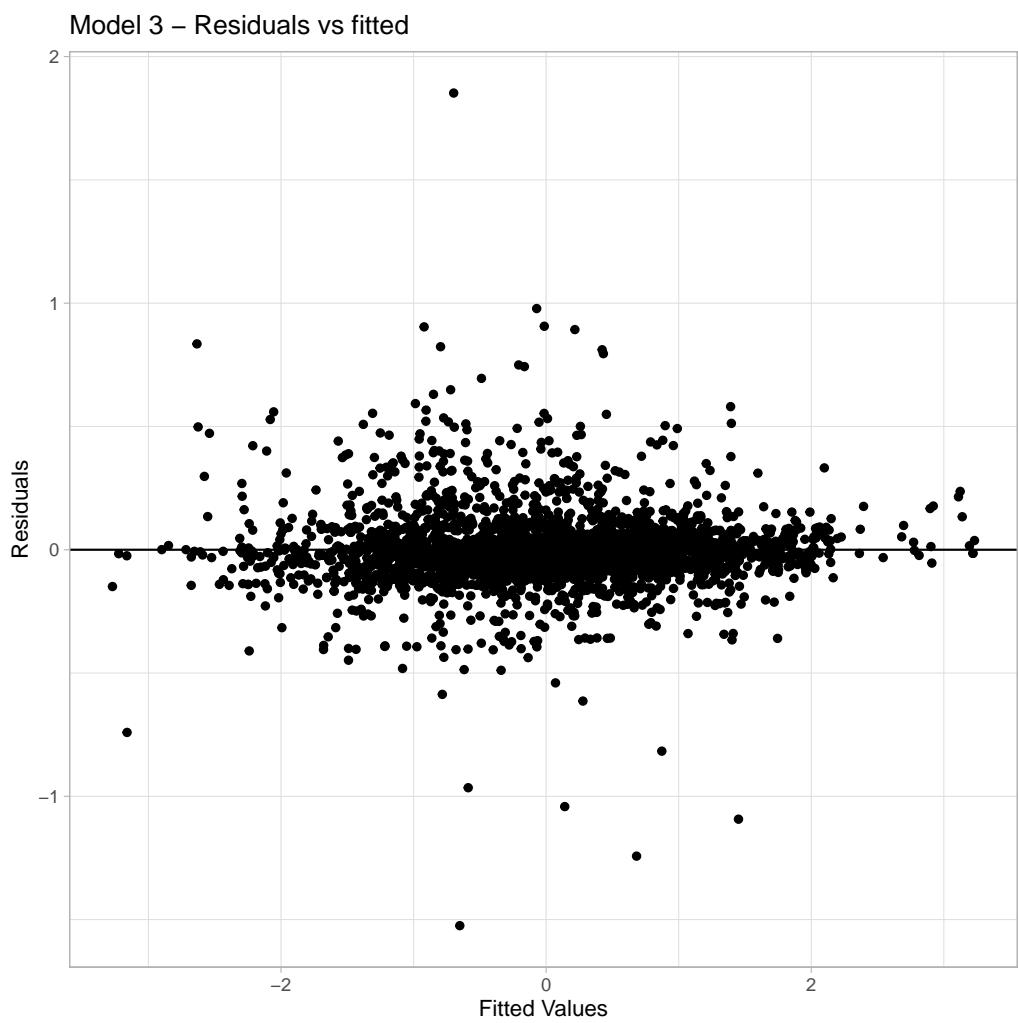


Figure A.10: Residuals vs fitted values for Model 3.

Model 4 – Normal QQ

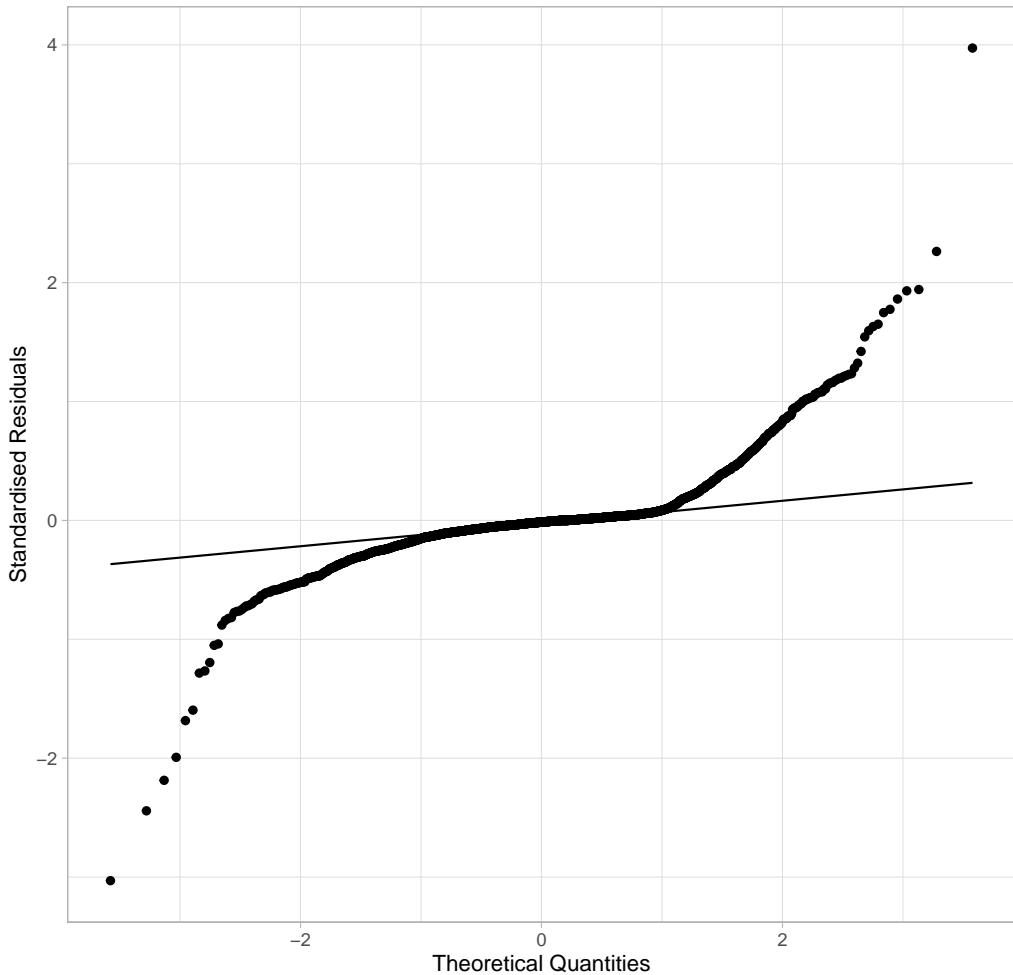


Figure A.11: QQ-plot of Model 4.

Model 4 – Residuals vs fitted

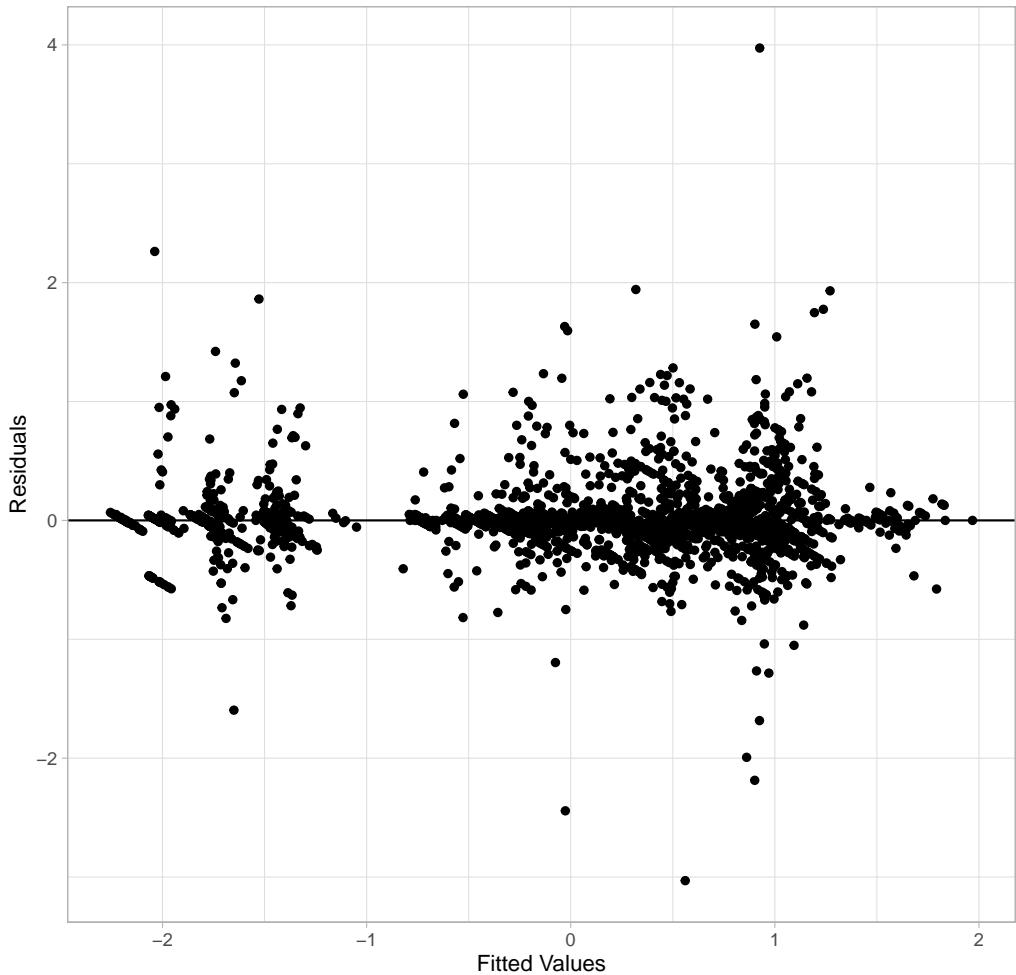


Figure A.12: Residuals vs fitted values for Model 4.

Model 5 – Normal QQ

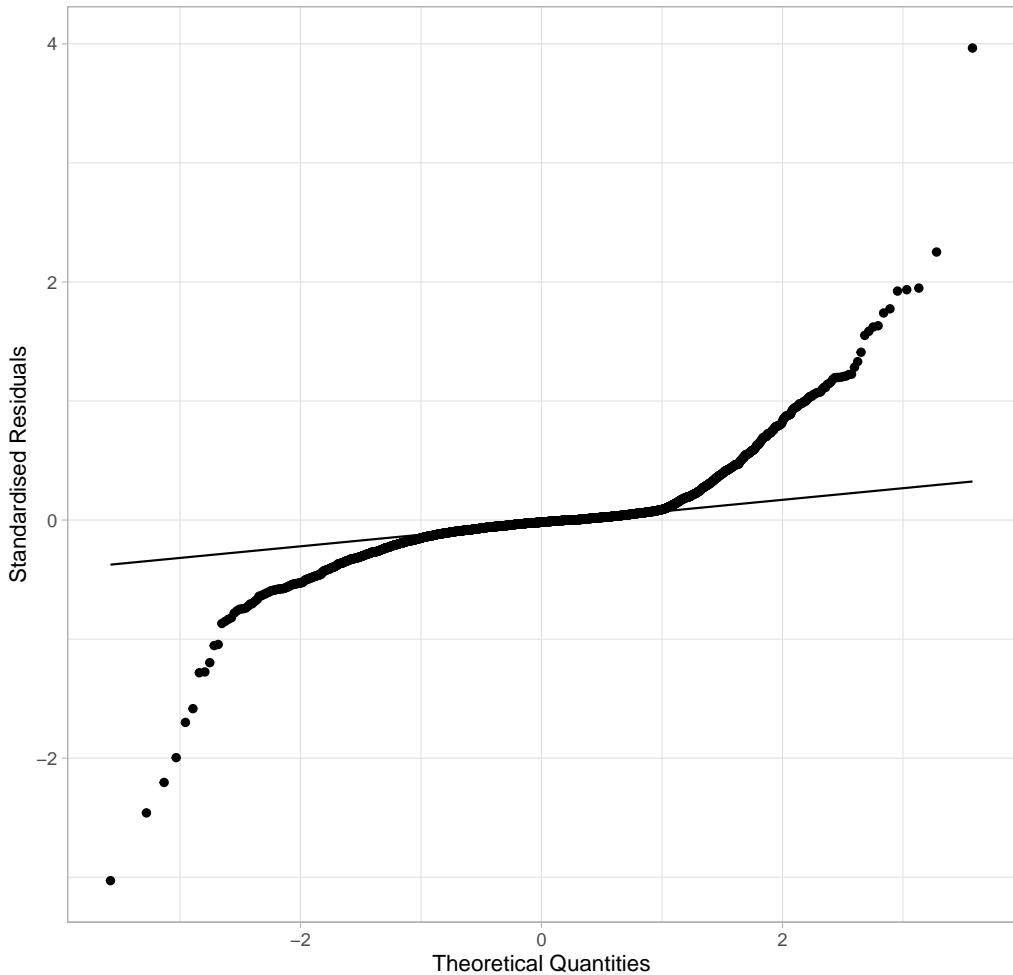


Figure A.13: QQ-plot of Model 5.

Model 5 – Residuals vs fitted

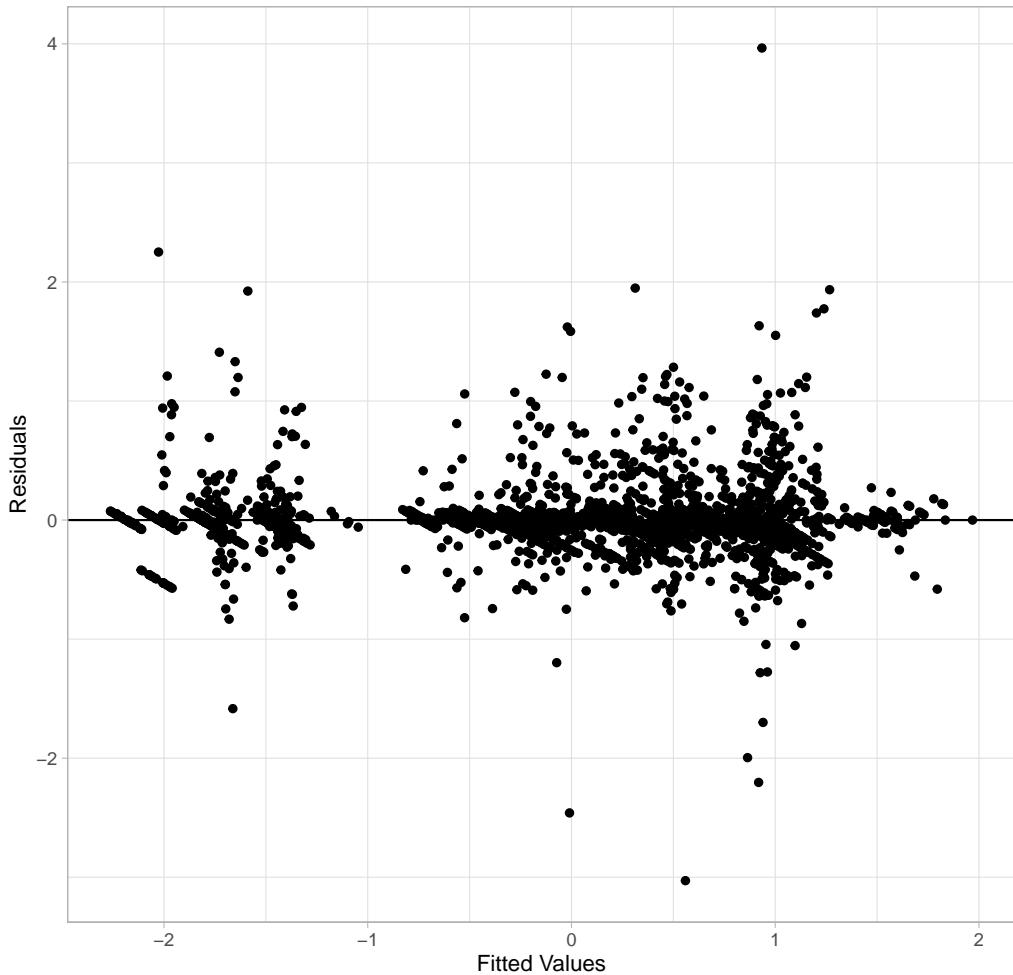


Figure A.14: Residuals vs fitted values for Model 5.