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English Weather and Rhine Wine Quality: An Ordered Probit Model

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Abstract *This paper analyses the quality of Rhine wine vintages from Schloss Johannisberg over the last 300 years. It draws on vintage lists and transforms the verbal qualitative assessments into five quality ranks. These ranks are related to temperature and precipitation data, using an ordered probit model. Since reliable instrumental weather data for the Rhine region do not exist for the time before 1826, we utilised the English Manley temperature series (beginning in 1659) and precipitation data for Kew Gardens (available from 1697 on). In addition, we used index data for Germany from the historical climate data bank Historische Klimadatenbank Deutschland of the University of Heidelberg. The results show that English weather is a good proxy variable for the actual weather conditions in the Johannisberg vineyards. While Frankfurt weather data yield a better goodness-to-fit, the data cover only half of the observation period. The models show that the biggest marginal temperature effects occur in the months May and September, i.e. during the blossoming and ripening periods. A 1 °C temperature increase for the entire growing season will increase the probability of harvesting a top vintage from approximately 20% to more than 50%. Therefore, the model suggests that moderate global warming is likely to improve the quality of Rhine wines.*

Introduction

Germany lies on the northernmost frontier of professional viticulture. Since vines must be protected from frost and certain necessary climatic conditions during the growing season must be met, virtually all the vineyards of Germany are located in the basin of the Rhine river and its tributaries.

Within the Rhineland area the Rheingau, confined by the villages of Bingen in the west and Hochheim in the east, is probably the best-known wine growing region. In fact, since the 17th century Rheingau wines have been the epitome of all Rhenish wines:[1] Hochheim was anglicised into ‘hock’ and, ever since, the word ‘hock’ has been used as a generic term for all Rhenish wines, wherever English is spoken (Simon and Hallgarten, 1963).

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Hocks have belonged to the most expensive wines and have been very popular especially in the UK. We know from Simon (1909) that hocks have been exported to England from the 13th century on.[2] Although they never reached the quantities of imported French wines—hocks were more expensive and were often subject to adulteration.

Within the Rheingau region, Schloss Johannisberg is arguably the oldest and most renowned wine estate. Founded in approximately 1100 as a monastery, it has been in church or aristocratic ownership ever since (Staab *et al.*, 2001). It is attributed with the discovery of the *Spätlese* (late harvest) and lent its name to the leading grape variety it grows: the riesling. Therefore, outside Europe the white riesling is also called Johannisberg riesling to avoid any confusion with other varieties.

The wines of Schloss Johannisberg have been enjoyed and praised by many people. For example, during his journey along the Rhine river in 1788, Thomas Jefferson wrote: "Stop on the road at the village of Rudesheim and the Abbaye of Johannisberg to examine their vineyards and wines. The latter is the best made on the Rhine without comparison, and it is about double the price of the oldest hock. That of the year 1775 is the best" (Staab *et al.*, 2001).

Jefferson's emphasis on a certain vintage exemplifies that not all vintages are equal: good wine years alternate with bad ones. Schloss Johannisberg has kept track of each vintage from the year 1700 up to the present time and has assessed its quality volatility by using descriptive terms such as *very good*, *mediocre*, or *poor*. Its vintage tables are the basis of this study.

This paper sets out to determine and quantify the factors that are crucial to wine quality differences at Schloss Johannisberg over a time period of 300 years (1700–2000). The analysis draws on a solid body of literature, mainly by Ashenfelter and collaborators, that has already examined the relationship between wine quality and weather (e.g. Ashenfelter and Byron, 1995; Ashenfelter *et al.*, 1995; Ashenfelter and Jones, 2000; Ashenfelter and Corsi, 2001; Jones and Storchmann, 2001; Ashenfelter and Storchmann, 2003; Haeger and Storchmann, 2005).[3] However, compared to the craft of viticulture, the instrumental measurement of temperature and precipitation is a very young discipline. The oldest time series data for the Rheingau region are available for Frankfurt, but do not begin before 1826. This lack of data might be remedied by resorting to English data, the so-called Manley series, which begins in 1659. This paper analyses whether English climate data are an appropriate proxy variable for local vineyard weather to explain quality variations of Schloss Johannisberg wines over the last 300 years. Or, in other words: is a rainy summer in London consistent with a bad vintage in Germany?

Data Situation and Sources

Assuming a close relationship between wine quality and weather, our primary focus must be on these variables. Wine quality can be measured and expressed in different ways. For example, German wine law states that a significant relationship between quality and specific sugar content in the wine must is to be measured in Oechsle degrees. The higher the Oechsle degrees, i.e. the higher the potential alcohol, the better the quality.

Wine critics disagree and claim wines are too complex to be judged by their sugar content alone. They claim that only the critic with his/her unique expertise, not a formula, is able to assess a wine's true quality. Thus, critical scores will reflect the wine quality in its entirety.

Finally, economists point to the role of prices as an unbiased quality indicator. After all, it is the consumer's willingness-to-pay that reveals the quality of a wine.

For the analysis on hand, none of the data mentioned above are available. Instead, we refer to the vintage tables of Schloss Johannisberg, which are published in Staab *et al.* (2001). These tables do not assign a number (score) but a qualitative attribute to each vintage. However, these attributes can be transformed into an ordinal ranking. Table 1 shows how attributes were aggregated and then assigned to a particular quality rank.

It must be emphasised that the ranks are merely an ordinal series. Thus, we are able to say that rank 1 is better than rank 2 but are unable to say to what extent. Additionally, the differences between the ranks do not have to be equidistant. For example, the distance between rank 1 and 2 can be much smaller than the one between rank 4 and rank 5, and vice versa.

Having computed the data it is tempting to calculate an average rank and look at its development over time. However, due to the ordinal character of the data the computation of an average value would be seriously flawed. Instead, Figure 1 shows how often a particular rank occurred within the past 25 years. For the sake of clarity we bundled rank 1 and 2 wines (good and very good vintages) and rank 4 and 5 wines (bad and very bad vintages) together. Looking at good and very good vintages shows that after a peak in the late 18th century, when more than half the vintages were rank 1 or 2, the number of top vintages declined to a low of less than 8 in 25 at the year 1900. After 1950, however, top vintages have become more frequent. In 2000, about half of all vintages since 1975 were good or very good. The curve for bad and very bad vintages reveals the reverse trend. After a phase when bad vintages were relatively rare (less than 7 out of 25), bad vintages occurred more often between 1800 and 1950. After 1950, however, there has rarely been a bad vintage. The average occurrence rate dropped from 9 to 1. Overall, Figure 1 shows that the quality of Schloss Johannisberg wines has varied a great deal over the last 300 years. However, the last 50 years have shown consistently higher qualities. The number of good vintages is higher than it has been since the mid 18th century and the number of bad vintages is lower than ever before.

In contrast to the data on wine quality, weather data for the desired region and time period are not readily available. In fact, there is no instrumental data series for the Rheingau region before 1826 and none for the entire European continent covering the entire period from1700 to 2000.[4] The only instrumental time series starting before 1700 exists for England. The so-called Manley temperature series for middle England starts in 1659 (Manley, 1974), and precipitation data for Kew Gardens in London begin in 1697 (Wales-Smith, 1971). Updated data for both series are down-

Table 1. Wine attributes and corresponding rank for Schloss Johannisberg wines

Rank	Attributes
Rank 1	Very good, top wine, extra good, trophy wine, particularly good, especially good, first rate top wine, good to very good, excellent
Rank 2	Good, quite good, average to good
Rank 3	Mediocre, drinkable, average, lesser to average, modest
Rank 4	Lesser wine, poor, sour
Rank 5	Not drinkable, very poor, acetic, extremely poor, unenjoyable

Source: Staab *et al.* (2001).

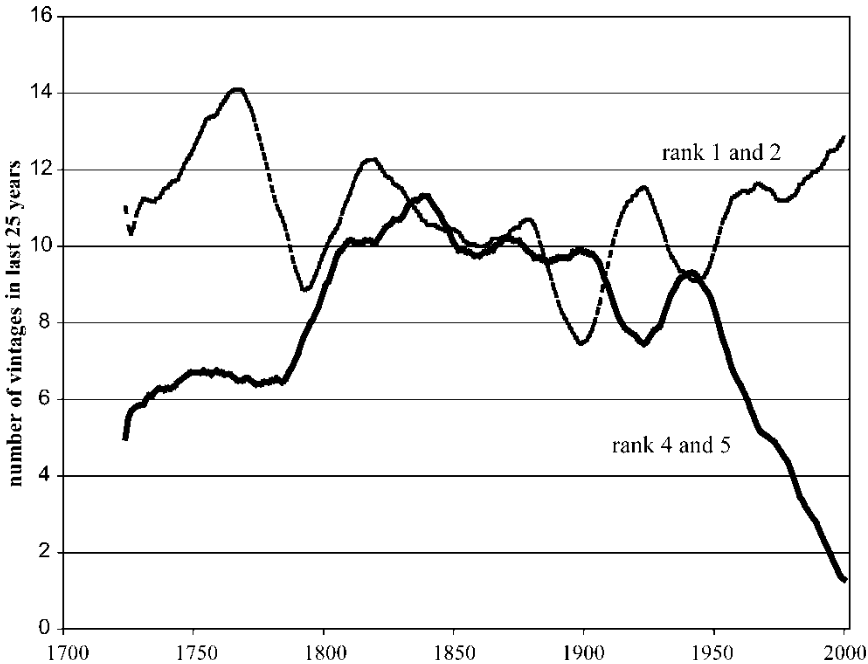

Figure 1. Development of wine quality: number of vintages occuring in last 25 years (moving 20 year average).

loadable from the database of the Royal Meteorological Institute of the Netherlands, the Koninklijk Nederlands Meteorologisch Instituut (KNMI) (van Oldenborgh, 2004).

The longest existing climate data series on the European continent comprises data for the Netherlands, which were computed by Labrijn (1945). The temperature series originates in De Bilt and begins with the year 1706; the precipitation series stems from Hoofddorp and begins in 1735. Both data series including their updates are downloadable from the KNMI Climate Explorer (van Oldenborgh, 2004).

Closer to the Rheingau region is the city of Frankfurt, for which temperature and precipitation data were computed beginning in 1826. The data are downloadable from the KNMI Climate Explorer (van Oldenborgh, 2004). Updates came from Deutscher Wetterdienst (the German Meteorological Service) and are available online at www.dwd.de.

There seems to be a trade-off between proximity and time coverage (i.e., degrees of freedom) (see also Figure 2). Only the English time series cover the entire time from 1700 to 2000. However, the linear distance between London and Schloss Johannisberg is approximately 375 km. De Bilt and Hoofddorp in the Netherlands lie closer to the Rheingau (234 km and 215 km, respectively) but the usage of these data requires the exclusion of 36 observation years. If referring to the Frankfurt data (31 km linear distance), we have to forgo almost half of the observation period.

In addition to these instrumental climate data, we can also draw on climate time series data developed by palaeoclimatologists. Historical climatology is aimed at broadening the understanding of weather and climate before the beginning of instrumental measurements. Drawing on non-instrumental man-made sources (e.g. records, documents, flood marks) and proxy variables (e.g. tree rings, ice core

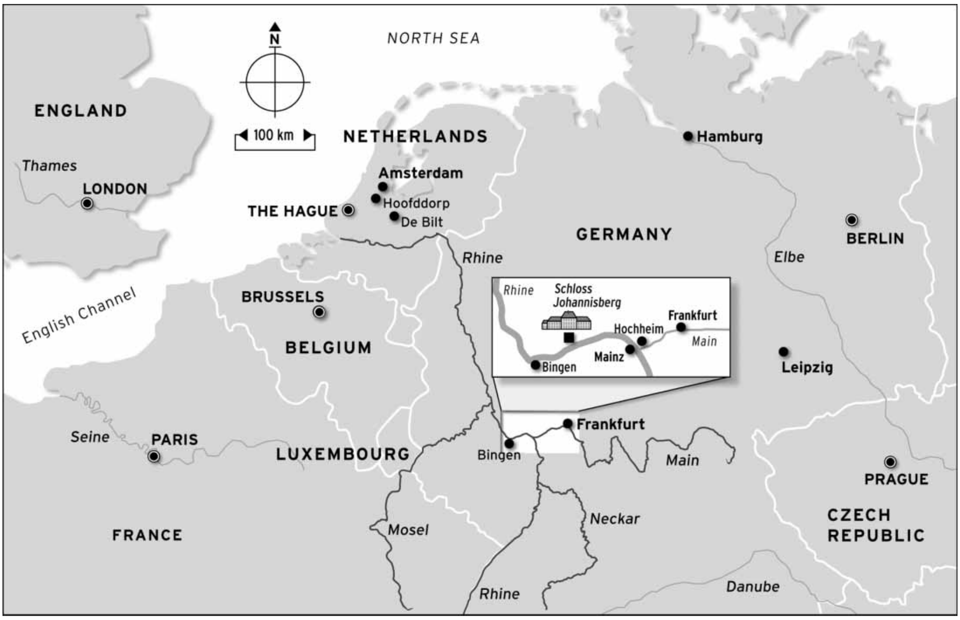

Figure 2. Western Europe and Schloss Johannisberg.

data) index data for temperature and precipitation back to the 15th century and before have been computed (see in detail Bradley, 1998; Brázdil *et al.*, 2004). For Germany, the historical climate data bank Historische Klimadatenbank Deutschland (HISKLID) at the University of Heidelberg provides monthly temperature and precipitation data starting with the year 1500 (Glaser, 1997, 2001; Glaser *et al.*, 1999).[5] The data do not refer to a particular location or region, but denote the average climate for all of Germany. Temperature and precipitation data are provided as indices and can take on seven values (+3, +2, +1, 0, −1, −2, −3), where the value 0 refers to the long-run average from 1901 to 1960. In this sense, an index of +3 denotes a month that is extremely warm or wet, respectively. Similarly, an index of −3 stands for a cold or dry month.[6] Since the indices are defined as standard deviations from the 1901–60 average (Glaser *et al.*, 1999), even real temperature and rainfall values can be derived. However, Pfister (1988) points out that the error margin for monthly values lies between 6% and 18%. The calculation of temperature and precipitation values may, therefore, lead to a pseudo-accuracy. Thus, in the following estimation, we will only refer to the index data.

Tables 2 and 3 show the descriptive statistics of the dependent variable and all monthly climate variables for England, Germany (index data), the Netherlands and Frankfurt.

Methods and Model

Given the discrete natural order of the independent variable and the fact that the differences between the ranks are not necessarily equivalent, the model is appropriately addressed by an ordered probit approach as first introduced by McKelvey and Zavoina (1975) (see also Davidson and MacKinnon, 1993; Greene, 2003). We can model the observed response by considering a latent (not observable) variable y_t^*,

Table 2. Descriptive statistics of ranks and climate variables for England and Germany, 1700–2000

	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
Rank	1	5	2.76	1.29				
	England (measured data)				*Germany (index data)*			
Temperature								
January	−3.1	7.5	3.28	1.95	−3	2	−0.09	0.97
February	−1.9	7.9	3.97	1.80	−3	2	−0.04	0.90
March	1.2	9.2	5.37	1.48	−3	2	−0.04	0.93
April	0.3	10.6	7.93	1.28	−3	3	0.00	0.99
May	8.6	15.1	11.26	1.15	−3	3	0.01	0.98
June	11.8	18.2	14.34	1.07	−3	3	−0.02	0.95
July	13.4	19.5	15.98	1.16	−3	3	−0.05	0.92
August	12.9	19.2	15.67	1.09	−3	3	−0.04	0.96
September	10.5	16.6	13.39	1.07	−3	3	0.00	0.92
October	5.3	13.3	9.70	1.27	−3	3	−0.09	0.96
November	2.3	10.1	6.07	1.38	−3	2	−0.08	0.94
December	−0.8	8.1	4.16	1.72	−3	3	−0.02	0.93
Precipitation								
January	2.5	136.7	48.83	27.21	−3	3	−0.29	1.52
February	2.0	127.0	39.58	23.67	−3	3	−0.28	1.26
March	0.8	118.4	39.82	23.18	−3	3	0.04	1.46
April	1.5	137.2	43.18	23.62	−3	3	−0.07	1.48
May	2.0	140.0	47.30	25.23	−3	3	−0.21	1.46
June	1.0	183.1	51.99	29.15	−3	3	−0.24	1.39
July	2.8	184.1	58.86	33.32	−3	3	0.00	1.41
August	0.5	165.6	56.89	29.82	−3	3	−0.26	1.38
September	1.8	147.3	55.43	31.13	−3	3	0.15	1.36
October	2.0	169.9	62.23	33.02	−2	3	0.37	1.29
November	6.9	189.0	59.51	31.55	−3	3	0.03	1.22
December	2.8	169.4	53.83	29.77	−3	3	−0.04	1.48

Source: See text.

which depends linearly on the explanatory variables x:

$$y_t^* = \mathbf{X_t \beta} + \varepsilon_t, \quad with\ \varepsilon_t \sim N(0, 1) \tag{1}$$

The observed category of y_t is based on y_t^* and can take on five values:

$$y_t = \left\{ \begin{array}{lll} 1 & if & y_t^* \leq \gamma_1 \\ 2 & if & \gamma_1 \leq y_t^* \prec \gamma_2 \\ 3 & if & \gamma_2 \leq y_t^* \prec \gamma_3 \\ 4 & if & \gamma_3 \leq y_t^* \prec \gamma_4 \\ 5 & if & \gamma_4 \leq y_t^* \end{array} \right\} \tag{2}$$

We emphasise that the actual values chosen to represent the categories in y are completely arbitrary. All the model requires is that larger category values correspond to larger values for the latent variable, so that $\gamma_t \prec \gamma_j$ implies that $y_t^* \prec y_j^*$.

Table 3. Descriptive statistics of climate variables for the Netherlands and Frankfurt

	Minimum	Maximum	Mean	Standard deviation	Minimum	Maximum	Mean	Standard deviation
	Netherlands (measured data)				*Frankfurt (measured data)*			
Temperature								
January	−7.0	6.2	1.28	2.71	−9.4	5.6	0.47	3.00
February	−6.4	7.6	2.46	2.39	−7.5	7.4	2.01	2.77
March	−2.3	8.8	4.59	1.85	−2.7	9.9	5.59	2.10
April	4.3	11.3	8.15	1.44	5.5	13.2	9.79	1.61
May	7.5	16.0	12.22	1.44	10.6	19.2	14.36	1.66
June	11.2	18.8	15.16	1.29	12.9	22.2	17.54	1.44
July	13.9	21.4	16.83	1.33	15.5	23.8	19.12	1.62
August	13.5	20.5	16.63	1.22	15.2	23.9	18.46	1.46
September	10.7	17.4	14.19	1.15	10.8	19.0	14.91	1.38
October	6.0	14.0	9.94	1.36	6.0	14.1	9.90	1.49
November	0.6	10.2	5.45	1.63	−1.0	9.4	5.02	1.77
December	−5.7	7.3	2.66	2.33	−7.9	7.1	1.85	2.50
Precipitation								
January	0.0	214.0	55.58	31.90	2.3	121.3	47.14	24.39
February	1.0	145.0	45.46	26.94	1.0	118.8	38.52	25.05
March	0.0	156.9	46.86	27.96	3.3	116.8	41.91	24.87
April	1.0	134.0	43.88	24.21	0.0	144.0	41.23	26.39
May	3.9	133.0	46.38	24.94	2.1	157.7	54.61	28.06
June	1.0	159.0	58.75	32.84	9.0	193.3	65.73	36.65
July	3.0	248.0	76.43	43.17	1.0	205.1	69.16	37.29
August	6.8	226.0	88.82	42.92	1.4	210.5	68.26	41.76
September	3.0	226.0	84.28	42.96	1.0	131.0	51.04	26.75
October	2.0	248.0	91.92	47.43	2.0	169.0	54.15	31.56
November	8.0	230.1	80.29	38.82	6.6	153.0	54.15	30.11
December	1.0	175.0	68.01	35.00	1.0	159.9	53.38	29.32

Source; See text. Temperature data begin in 1706 (Netherlands) and 1757 (Frankfurt), respectively. Precipitation data begin in 1735 (Netherlands) and 1826 (Frankfurt), respectively.

The probability of y_i being in a particular rank can then be estimated as:

$$\begin{aligned}\Pr(y_t = 1) &= \Pr(y_t^* < \gamma_1) = \Pr(\mathbf{X_t\beta} + \varepsilon_t < \gamma_1) \\ &= \Pr(\varepsilon_t < \gamma_1 - \mathbf{X_t\beta}) = \Phi(\gamma_1 - \mathbf{X_t\beta})\end{aligned} \tag{3}$$

$$\begin{aligned}\Pr(y_t = 2) &= \Pr(\gamma_1 \leq y_t^* < \gamma_2) = \Pr(\gamma_1 \leq \mathbf{X_t\beta} + \varepsilon_t < \gamma_2) \\ &= \Pr(\varepsilon_t < \gamma_2 - \mathbf{X_t\beta}) - (\varepsilon_t \leq \gamma_1 - X_t\beta) \\ &= \Phi(\gamma_2 - \mathbf{X_t\beta}) - \Phi(\gamma_1 - \mathbf{X_t\beta})\end{aligned}$$

. . ., etc. and

$$\begin{aligned}\Pr(y_t = 5) &= \Pr(y_t^* \geq \gamma_4) = \Pr(\mathbf{X_t\beta} + \varepsilon_t \geq \gamma_4) \\ &= \Pr(\varepsilon_t \geq \gamma_4 - \mathbf{X_t\beta}) = \Phi(\mathbf{X_t\beta} - \gamma_4)\end{aligned}$$

where $\Phi(.)$ denotes the respective cumulative distribution function.

The latent variable y_t^* can then be estimated as follows:

$$y_t^* = \sum_{i=1}^{12} \beta_i temp_t + \sum_{j=1}^{12} \beta_j prec_t + \beta_k trend_t + \beta_m dum_t \quad (4)$$

We regress the latent variable on 12 monthly temperature (*temp*) and precipitation (*prec*) variables. Since harvest normally occurs in October, November and December weather data of year *t* cannot affect the wine quality of vintage *t* anymore. Thus, November and December weather data were included as last year's values. Drawing on the findings of Ashenfelter et al. (1995) and Jones and Storchmann (2001) for Bordeaux wines as well as on Ashenfelter and Storchmann (2003) for Mosel wines, we expect y_t^* to be positively correlated with monthly temperature values. This should be particularly true for the growing season, i.e. the months from April to October. Similarly, rainfall is assumed to be beneficial if it occurs during winter months that precede the harvest, i.e. from November (in the year prior to the harvest) to March. Any other precipitation, especially during the harvest itself, is expected to have adverse quality effects. Given the nature of the order, i.e. lower ranks denote better quality, negative signs indicate a beneficial influence on quality and vice versa.

The fact that the quality assessments lack an objective measure and are, therefore, more or less subjective raises the question of whether a rating that encompasses more than three centuries can be consistent over time. For example, Pfister (1988) speculates that wine quality ratings were more lenient in the past than they are now. Wright (1968), on the other hand, finds a close relationship between subjective qualitative ratings and objective measures (e.g. the wine must weight measured in Oechsle degrees) for wines from Luxembourg for 1838 to 1965. Given this issue, we introduced a trend variable (*trend*) that accounts for a possible 'rate deflation'. Hence, in the case of stricter assessments over time the trend variable should take on a positive value. Finally, we inserted a dummy variable (*dum*) for three vintages (1709, 1716, 1816) that were so poor in quality and/or quantity that a harvest was not worthwhile.

Results

Table 4 shows the estimation results of the above models for different weather data and time periods. On the one hand, the time period covered by the models decreases from the left to the right. While the estimates using instrumental data for England cover the entire time period from 1700 to 2000, the model based on Frankfurt data ranges only from 1827 to 2000. On the other hand, while the time covered becomes shorter, the distance to the vineyards of Schloss Johannisberg decreases. Thus, given their proximity, weather data for Frankfurt might be the better proxy variable for the actual weather within the vineyards.

Overall, all estimates show that wine quality ranks are significantly determined by climatic variations. In general, warm conditions during the growing season from April to October are beneficial to quality. All parameters for temperature variables show negative signs and most of them are significant. Not surprisingly, given the size of the estimated parameters,[7] all models highlight the importance of the months May and September, i.e. the vine blossom and the ripening period.

Precipitation during the growing season appears to have a negative effect on wine quality. Thus, all estimates show positive signs. However, compared to the temperature variables, rainfall variables are less significant. Only the model based on German index

Table 4. Results of ordered probit models for quality ranks

	England, 1700–2000 ($n = 299$)	Germany, 1700–1995 ($n = 296$)	Netherlands, 1736–2000 ($n = 265$)	Frankfurt, 1827–2000 ($n = 166$)
Temperature				
January	−0.002 (−0.05)	−0.053 (−0.66)	−0.017 (−0.54)	0.071 (1.75)
February	0.016 (0.42)	0.013 (0.15)	0.028 (0.71)	0.020 (0.52)
March	−0.002 (−0.04)	−0.076 (−1.06)	−0.007 (−0.16)	−0.038 (−0.81)
April	−0.081 (−1.61)	−0.124 (−1.68)	−0.202** (−4.02)	−0.154** (−2.56)
May	−0.295** (−4.41)	−0.398** (−5.73)	−0.390** (−7.14)	−0.271** (−4.98)
June	−0.153** (−2.43)	−0.071 (−0.87)	−0.199** (−3.51)	−0.152** (−2.51)
July	−0.243** (−3.45)	−0.044 (−0.49)	−0.139* (−2.20)	−0.111 (−1.66)
August	−0.081 (−1.11)	−0.064 (−0.75)	−0.037 (−0.52)	−0.229** (−2.69)
September	−0.229** (−3.60)	−0.183* (−2.03)	−0.236** (−3.27)	−0.380** (−4.90)
October	−0.161** (−2.81)	−0.243** (−3.33)	−0.154** (−2.71)	−0.122 (−1.67)
November ($t-1$)	0.079 (1.42)	0.049 (0.72)	0.057 (1.21)	0.043 (0.66)
December ($t-1$)	−0.022 (−0.09)	−0.177** (−2.42)	−0.089** (−2.51)	−0.039 (−0.68)
Precipitation				
January	0.003 (1.25)	0.041 (0.88)	0.004 (1.65)	0.004 (0.79)
February	0.004 (1.39)	−0.062 (−0.96)	0.001 (0.21)	−0.006 (−1.50)
March	−0.003 (−0.88)	−0.067 (−1.45)	0.004 (1.47)	0.000 (0.10)
April	−0.002 (−0.72)	0.099* (2.04)	0.005 (1.67)	0.002 (0.56)
May	−0.002 (−0.67)	0.030 (0.65)	−0.003 (−0.96)	0.003 (1.04)
June	0.003 (1.31)	0.063 (1.22)	0.003 (1.47)	0.006* (2.20)
July	0.001 (0.53)	0.203** (4.06)	0.006** (2.80)	0.002 (0.80)
August	0.006** (2.57)	0.107* (2.04)	0.006** (3.57)	0.003 (1.42)
September	0.002 (0.81)	0.123** (2.37)	0.003 (1.73)	0.008* (2.07)
October	−0.001 (−0.50)	0.109* (2.27)	0.003 (1.76)	0.004 (1.61)
November ($t-1$)	−0.000 (−0.16)	−0.096 (−1.79)	0.001 (0.44)	−0.004 (−1.49)
December ($t-1$)	−0.000 (−0.09)	−0.000 (−0.00)	0.002 (0.98)	0.006 (1.74)
Trend	−0.000 (−0.35)	−0.001 (−0.92)	−0.000 (−0.30)	−0.001 (−0.60)
Dummy variable	9.369** (30.54)	8.170** (28.60)	7.110** (20.35)	—
γ_1	−16.024** (−8.71)	−1.179** (−7.23)	−15.974** (−8.10)	−21.068** (−9.35)
γ_2	−15.101** (−8.31)	−0.248 (−1.60)	−14.913** (−7.71)	−19.901** (−9.00)
γ_3	−14.196** (−7.91)	0.673** (4.12)	−13.980** (−7.29)	−18.640** (−8.56)
γ_4	−13.392** (−7.52)	1.482** (7.99)	−13.051** (−6.89)	−17.577** (−8.22)
Akaike information criterion	2.843	2.821	2.709	2.596
Log likelihood	−395.1	−387.5	−329.0	−186.5
Restr. log likelihood	−471.4	−467.3	−417.7	−257.7
LR statistic	152.7	159.6	177.5	142.3
Pseudo − R^2 (%)[a]	16.20	17.08	21.24	27.62

Note: Heteroscedasdicity-consistent (Huber–White) t-values in parentheses.
**Significant at the 2% level; *significant at the 5% level.
[a]Likelihood ratio index according to McFadden (1974).

data shows a significantly negative effect throughout almost the entire growing season. All other models yield significant effects only for selected months.

The trend variable, which was inserted to capture possible time inconsistencies of the ranking (rank deflation/inflation), is insignificant in all models. Thus, we abandon the hypothesis that wine was judged more leniently in the past than it is today.

All four models show a satisfactory goodness-to-fit. The likelihood ratio indices or pseudo-R^2 values (McFadden, 1974) range between 16.2% for the model based on

English data and 27.6% for the model based on Frankfurt data. The model based on Dutch data yields, according to its geographical position between England and the Rheingau, a pseudo-R^2 that is between these values (21.2%).

Surprisingly, there is almost no difference in the goodness-to-fit between the first two models. That is, English weather data provide wine quality predictions that are as good as equations based on index data for Germany. Apparently, a country-wide index that also covers parts of eastern Germany, with its rather continental climate, has no advantage over a remote maritime climate proxy variable such as the English data. However, these results indicate that, overall, proximity improves the explanatory value of the proxy variables temperature and precipitation.

Table 5 shows the quality rank (*ex post*) predictions and deviations of each model by rank. Using English weather data 39.8% of all quality ranks were predicted correctly and 42.8% were predicted with a deviation of 1 rank. Only 2.0% of all vintages were

Table 5. Prediction and deviation by rank

	Deviation by rank					
	0	1	2	3	4	Sum
			England (instrumental data 1700–2000)			
Rank 1	31	17	13	0	0	61
Rank 2	24	47	0	2	0	73
Rank 3	45	27	6	0	0	78
Rank 4	6	34	9	1	0	50
Rank 5	13	3	18	2	1	37
Sum	119	128	46	5	1	299
Percentage	39.8	42.8	15.4	1.7	0.3	
			Germany (index data 1700–1995)			
Rank 1	38	14	8	0	0	60
Rank 2	25	44	0	1	0	70
Rank 3	42	25	11	0	0	78
Rank 4	6	39	4	2	0	51
Rank 5	18	1	13	3	2	37
Sum	129	123	36	6	2	296
Percentage	43.6	41.6	12.2	2.0	0.7	
			Netherlands (instrumental data 1736–2000)			
Rank 1	32	16	3	1	1	53
Rank 2	32	31	3	0	0	66
Rank 3	22	41	4	0	0	67
Rank 4	13	26	9	0	0	48
Rank 5	13	10	6	1	1	31
Sum	112	124	25	2	2	265
Percentage	42.3	46.8	9.4	0.8	0.8	
			Frankfurt (instrumental data 1827–2000)			
Rank 1	23	8	4	0	0	35
Rank 2	13	26	0	0	0	39
Rank 3	30	15	2	0	0	47
Rank 4	15	14	1	0	0	30
Rank 5	3	6	5	1	0	15
Sum	84	69	12	1	0	166
Percentage	50.6	41.6	7.2	0.6	0.0	

Source: See text.

forecast 3 or more ranks off their actual value. Distinguishing wine quality ranks, it can be seen that the model predicts 31 of 61 (50.8%) rank 1 vintages correctly. However, only 35% of rank 5 vintages were predicted correctly. In contrast, the Frankfurt model predicts 50.6% of all vintages correctly and 41.6% with a deviation of 1 rank. Only 0.6% of all predictions deviate by 3 ranks or more from the respective actual value. Interestingly, in forecasting the worst vintages the Frankfurt model cannot outperform the model based on English data: only 20% of all rank 5 vintages were predicted correctly.

The estimated coefficients of the ordered model must be interpreted with care (e.g. Greene, 2003). The sign of $\hat{\boldsymbol{\beta}}$ shows the direction of the change in the probability of falling in the endpoint rankings ($y_t = 1$) and ($y_t = 5$) when $\mathbf{X}$ changes. $\Pr(y_t = 1)$ changes in the opposite direction of the sign of $\hat{\boldsymbol{\beta}}$ and $\Pr(y_t = 5)$ changes in the same direction as the sign of $\hat{\boldsymbol{\beta}}$. The effects on the probability of falling in any of the middle rankings are unclear, *a priori*. The changes in the respective probabilities are:

$$\frac{\partial \Pr(y_t = 1)}{\partial \mathbf{x_i}} = -\phi(\mathbf{x_i}\boldsymbol{\beta})\boldsymbol{\beta} \tag{5}$$

$$\frac{\partial \Pr(y_t = 2)}{\partial \mathbf{x_i}} = [\phi(-\mathbf{x_i}\boldsymbol{\beta}) - \phi(\gamma_1 - \mathbf{x_i}\boldsymbol{\beta}]\boldsymbol{\beta}$$

$$\ldots$$

$$\frac{\partial \Pr(y_t = 5)}{\partial \mathbf{x_i}} = \phi(\gamma_4 - \mathbf{x_i}\boldsymbol{\beta})\beta$$

where $\phi(.)$ denotes the standard normal density function.

Table 6 reports the marginal effects of the models. For the sake of clarity, we confine our attention to the England and Frankfurt model and only to those variables with the greatest significance, i.e. temperatures during the growing season (April to October). Since the marginal effects depend on the level of all variables, we computed them at the mean values of all variables ($\bar{x}$). We calculated the marginal effect as the percentage change in the probability of being in a particular rank due to a 1 °C increase in the monthly average temperature.

The first line in Table 6 gives the probability that a vintage is in a particular quality rank given average temperature and precipitation. Even though the average is based

Table 6. Effects of temperature increases on probabilities: increase by 1 °C

	England					Frankfurt				
	Rank					Rank				
	1	2	3	4	5	1	2	3	4	5
Average probability (%)	20.4	24.4	26.4	16.5	12.4	21.0	23.2	29.4	17.4	9.0
	Percentage change in probability									
April (4)	1.7	0.7	−0.4	−0.9	−1.1	2.5	1.1	−0.5	−1.5	−1.6
May (5)	6.8	2.1	−1.8	−3.3	−3.7	4.5	1.9	−1.0	−2.7	−2.7
June (6)	3.4	1.2	−0.8	−1.7	−2.1	2.5	1.1	−0.5	−1.5	−1.6
July (7)	5.5	1.8	−1.4	−2.7	−3.2	1.8	0.8	−0.3	−1.1	−1.2
August (8)	1.8	0.7	−0.4	−0.9	−1.1	3.8	1.6	−0.8	−2.3	−2.4
September (9)	5.2	1.7	−1.3	−2.6	−3.0	6.5	2.6	−1.6	−3.8	−3.6
October (10)	3.6	1.3	−0.9	−1.8	−2.2	2.0	0.9	−0.4	−1.2	−1.3
Growing season (4–10)	33.9	0.3	−12.6	−12.0	−9.6	29.2	3.5	−11.8	−12.7	−8.2

on different time periods, i.e. Frankfurt's average refers to 166 observations, whereas England's average is based on 299 observations, the numbers are very similar. For example, given an average year, the likelihood of a given vintage being ranked number 1 is 20.4% using the England model and 21.0% using Frankfurt data. Regarding rank 2 this is 24.4% and 23.2%, respectively.

The next lines report changes in these probabilities due to a temperature increase by 1 °C separately for each month and, eventually, for the growing season in its entirety. Note that the percentage changes add up to 0. According to the estimated parameters given in Table 4, both models emphasise the importance of the months May and September for wine quality. A 1 °C temperature increase in these months will increase the probability of a given vintage to be ranked number 1 by 4.5–6.8%. For example, if the average May temperature in England is 1 °C above the long-term mean of 11.26 °C (see Table 2), the probability that the entire vintage will be ranked number 1 will increase from 20.4% to 27.2%. At the same time, the likelihood that the vintage will be ranked number 5 will fall from 12.4% to 9.1%.

Table 7. Best 30 vintages between 1700 and 2003: percentage probability of being in quality rank 1

	English weather data (from 1700 on)			Frankfurt weather data (from 1827 on)		
Number	Vintage	Percentage	Actual rank	Vintage	Percentage	Actual rank
1	1959	91.2	1	1947	100.0	1
2	1947	89.2	1	2003	99.5	—[a]
3	1949	85.9	1	1865	99.4	1
4	1989	83.7	3	1827	97.8	1
5	1976	82.6	1	1999	97.4	1
6	1911	80.7	1	1997	91.7	2
7	1727	75.9	1	1911	91.2	1
8	1921	74.3	1	1868	90.2	1
9	1933	74.2	1	1857	88.0	1′
10	1826	71.6	1	1859	87.6	1
11	1779	70.8	1	1964	84.9	1
12	2003	70.0	—[a]	1959	83.0	1
13	1780	69.7	2	2002	81.5	—[a]
14	1868	66.7	1	1858	80.1	1
15	1798	65.6	1	1949	79.6	1
16	1995	64.5	3	1945	77.5	1
17	1818	64.2	2	1929	76.5	1
18	1759	63.4	1	1921	71.2	1
19	1945	62.2	1	1989	69.0	3
20	1865	60.1	1	1937	67.0	1
21	2001	59.4	—[a]	1942	64.7	2
22	1804	59.4	2	2000	64.3	2
23	1934	59.1	1	1953	63.3	1
24	1999	58.8	1	1992	62.8	2
25	1983	57.3	2	1846	58.9	1
26	1827	57.2	1	1993	57.9	1
27	1831	54.3	1	1934	57.1	1
28	1825	53.9	1	1976	55.9	1
29	1731	53.8	2	1991	55.6	2
30	1730	51.9	5	1895	53.9	2

Source: See text.
[a]*Ex ante* forecast.

Temperature variations are not only interesting on a month-to-month basis. Often the entire growing season deviates from the long-term average. In fact, there is some evidence that global warming already has significantly increased growing season temperatures around the globe.[8] For the Rhine valley, climatologists predict a further increase by 1 °C until the year 2050. Jones *et al.* (2005) predict that global warming will be beneficial to the quality of Rhine wines due to an extended maturation period.[9] Our model supports these findings. As reported in Table 6, the percentage changes in the probabilities of both models forecast that then about half of all vintages will be ranked number 1. The likelihood of the occurrence of a very bad vintage will drop from about 10% to 1–2%.

Finally, we employ the models for an *ex post/ex ante* forecast to pinpoint the best vintages of the last three centuries and relate the wine years 2001, 2002 and 2003 to them. As disclosed in Table 7, despite a few prediction problems,[10] both models regard more or less the same vintages as very good. This is particularly true for 1947, 1865, 1827, 1999, 1911, 1959 and 1949. An *ex ante* forecast predicts that 2003 is one of the best vintages of the last 300 years, second only to 1947. In addition, 2002 and 2001 appear to be very good wine years.

Summary

In this paper we analysed the quality of Rhine wine vintages from Schloss Johannisberg over the last 300 years. We drew on vintage lists provided by Schloss Johannisberg and transformed the verbal qualitative assessments into five quality ranks. Referring to prior studies on wine quality we focused on weather, i.e. temperature and precipitation, as crucial independent variables. Since reliable instrumental weather data for the Rhine region do not exist for the time before 1826, we resorted to Dutch data (starting at 1736) and English data. The English Manley temperature series begins in 1659; precipitation data for Kew Gardens are available from 1697 on. In addition, we used temperature and rainfall index data for Germany from the historical climate data bank HISKLID of the University of Heidelberg.

The nature of the quality ranks as ordered discrete variables is appropriately addressed by an ordered probit model. We regressed this model using the different climate data. It was shown that English weather is a good proxy variable for the actual weather conditions in the Johannisberg vineyards. However, greater proximity to the vineyards leads to an improvement in the goodness-to-fit values. Thus, Frankfurt weather data are the most appropriate data to explain Rhine wine quality (but are not available for the entire observation period).

All models show that the biggest marginal temperature effects occur in the months May and September, i.e. during blossom and the ripening period. For example, a 1 °C increase in the mean May temperature will increase the probability of a given vintage to be ranked number 1 from about 20% to more than 25%. The same temperature increase for the entire growing season will increase the chances of yielding a top vintage from about 20% to more than 50%. Therefore, moderate global warming is likely to improve the quality of Rhine wines.

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Notes

1. The term 'Rhenish wines' was also used for the wines from Alsace (Bassermann-Jordan, 1923; Unwin, 1991).
2. Even now, almost 50% of all German wine exports go to the UK (Storchmann and Schamel, 2004).
3. In contrast, Weger (1952) analysed the relationship between Schloss Johannisberg's wine quality and the number of sun spots, but could find no relation.
4. A comprehensive overview of regional time series of instrumental weather data available is provided by von Rudloff (1967). More recent sources are given in Brázdil *et al.* (2004).
5. HISKLID is part of the European historical climate data bank EURO-CLIMHIST at the University of Bern, Switzerland (Pfister *et al.*, 1999).
6. All data were provided by Professor Rüdiger Glaser of the Department of Geography at the University of Heidelberg, Germany.
7. However, as will be discussed below, estimated parameters cannot be directly translated into marginal effects.
8. See Jones *et al.* (2005) and the there quoted literature.
9. In contrast, other wine-growing regions are already at (e.g. Bordeaux) or even beyond (e.g. Rioja) their temperature optimum (Jones *et al.*, 2005). A further temperature increase will result in 'flabby' high-alcohol and low-acidity wines.
10. Both models predict that the year 1989, a number 3 ranked vintage, was a top year. In addition, the model using English data deemed 1730 (rank 5) a very good year.

References

ASHENFELTER, O. and BYRON, R. (1995) Predicting the quality of an unborn grange, *Economic Record*, 71(212), 40–53.

ASHENFELTER, O. and CORSI, A. (2001) Predicting Italian wine quality from weather data and expert's ratings, in: PICHERY, M. and TERRAZA, M. (eds) Oenometrics VII. 7th annual meeting of the Vineyard Data Quantification Society in Montpellier. *Cahier Scientifique* No. 4 (July 2001). Faculté des sciences économiques, Université de Montpellier.

ASHENFELTER, O. and JONES, G. (2000) The demand for expert opinion: Bordeaux wine, in: PICHERY, M. and TERRAZA, M. (eds) Oenometrics VI. 6th annual meeting of the Vineyard Data Quantification Society in Ajaccio, Corsica. *Cahier Scientifique* No. 3 (March 2000), Faculté des sciences économiques, Université de Montpellier.

ASHENFELTER, O. and STORCHMANN, K. (2003) Are Mosel wine prices determined by experts or fundamentals?, paper presented at Oenometrie X: 10th annual meeting of the Vineyard Data Quantification Society, Budapest.

ASHENFELTER, O., ASHMORE, D. and LALONDE, A. (1995) Bordeaux wine vintage quality and the weather, *Chance*, 8(4), 7–15.

BASSERMANN-JORDAN, F. VON (1923) *Geschichte des Weinbaus*, vols 1 and 2, Frankfurt: Frankfurter Verlags-Anstalt.

BRADLEY, R. (1998) *Paleoclimatology. Reconstructing Climates of the Quaternary*, 2nd edn, San Diego, CA: Harcourt Academic Press.

BRÁZDIL, R., PFISTER, C., WANNER, H., STORCH, H. VON and LUTERBACHER, J. (2004) Historical climatology in Europe—the state of the art, *Climatic Change*, 70, 363–430.

DAVIDSON, R. and MACKINNON, J. (1993) *Estimation and Inference in Econometrics*, Oxford: Oxford University Press.

GLASER, R. (1997) On the course of temperature in central Europe since the year 1000 AD, *Historical Social Research*, 22, 59–87.

GLASER, R. (2001) *Klimageschichte Mitteleuropa. 1000 Jahre Wetter, Klima, Katastrophen*, Darmstadt: Primus Verlag.

GLASER, R., BRÁZDIL, R., PFISTER, C., DOBROVOLNÝ, P., BARRIENDOS VALLVÉ, M., BOKWA, A., CAMUFFO, D., KOTYZA, O., LIMANÓWKA, D., RÁCZ, L. and RODRIGO, F. (1999) Seasonal temperature and precipitation fluctuations in selected parts of Europe during the sixteenth century, *Climatic Change*, 43, 169–200.

GREENE, W. (2003) *Econometric Analysis*, 5th edn, Upper Saddle River, NJ: Prentice Hall.

HAEGER, J. and STORCHMANN, K. (2005) Prices of American Pinot Noir wines: climate, craftsmanship, critics. *Agricultural Economics*, Forthcoming.

JONES, G. and STORCHMANN, K. (2001) Wine market prices and investment under uncertainty: an econometric model for Bordeaux crus classés, *Agricultural Economics*, 26, 115–133.

JONES, G., WHITE, M., COOPER, O. and STORCHMANN, K. (2005) Climate change and global wine quality, *Climatic Change* (in press).

LABRIJN, A. (1945) *Het Klimaat van Nederland Gedurende de Laatste Twee en Halve Eeuw*, Schiedam: Kon. Ned. Boekdrukkerij H. A. M. Roelants.

MANLEY, G. (1974) Central England temperatures: monthly means, 1659 to 1973, *Quarterly Journal of the Royal Meteorological Society*, 100, 389–405.

MCFADDEN, D. (1974) The measurement of urban travel demand, *Journal of Public Economics*, 3, 303–328.

MCKELVEY, R. and ZAVOINA, W. (1975) A statistical model for the analysis of ordinal level dependent variables, *Journal of Mathematical Sociology*, 4, 103–120.

OLDENBORGH, G. VAN (2004) KNMI Climate Explorer. Available at http://climexp.knmi.nl/.

PFISTER, C. (1988) *Klimageschichte der Schweiz 1525–1860*, 3rd edn, Bern: Verlag Paul Haupt.

PFISTER, C., BRÁZDIL, R., GLASER, R., PFISTER, C., BRÁZDIL, R., GLASER, R., BARRIENDOS, M., CAMUFFO, D., DEUTSCH, M., DOBROVLNÝ, P., ENZI, S., GUIDOBONI, E., KOTYZA, O., MILITZER, S., RÁCZ, L. and RODRIGO, F. (1999) Documentary evidence on climate in sixteenth century Europe, *Climatic Change*, 43, 55–110.

PIGOTT, S. (1995) *The Wine Atlas of Germany*, London: Mitchell Beazley.

RUDLOFF, HANS VON (1967) *Die Schwankungen und Pendelungen des Klimas in Europa seit dem Beginn der regelmässigen Instrumenten-Beobachtungen (1670)*, Braunschweig: Friedrich Vieweg & Sohn.

SIMON, A. (1909) *The History of the Wine Trade in England*, vols 1–3, London: Wyman & Sons.

SIMON, A. and HALLGARTEN, S. (1963) *The Great Wines of Germany and its Famed Vineyards*, New York: McGraw-Hill.

STAAB, J., SEELINGER, H. and SCHLEICHER, W. (2001) *Schloss Johannisberg. Nine Centuries of Wine and Culture on the Rhine*, Mainz: Woschek-Verlag.

STORCHMANN, K. and SCHAMEL, G. (2004) Germany, in: ANDERSON, K. (ed.) *The World's Wine Market. Globalization at Work*, Cheltenham: Edward Elgar, 110–123.

UNWIN, T. (1991) *Wine and the Vine. An Historical Geography of Viticulture and the Wine Trade*, London: Routledge.

WALES-SMITH, G. (1971) Monthly and annual totals of rainfall representative of Kew, Surrey, for 1697 to 1970, *Meteorological Magazine*, 100, 345–362.

WEGER, N. (1992) *Weinernten und Sonnenflecken. Berichte des deutschen Wetterdienstes in der US-Zone*, 38, 229–237, Bad Kissingen.

WRIGHT, P. (1968) Wine harvests in Luxembourg and the biennial oscillation in European summers, *Weather*, 23, 300–304.