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Bordeaux wine quality and climate fluctuations during the last century: changing temperatures and changing industry

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ABSTRACT: Recent studies have shown a generalized impact of multi-decadal climatic variability on the growing-quality of world wines during the twentieth century. This information has been used to predict the effects of climate change, mainly rising temperatures, on the future spatial distribution of wine regions and constraints on wine quality. On the other hand, some wine experts have identified the adaptive technological revolution of the wine industry as the main factor explaining rising wine quality; however, this hypothesis remains untested. Here, a time-varying coefficients regression approach is developed that is capable of partitioning the temporal effects of temperature on wine quality across sequential grape growing seasons, accounting for wine-rating uncertainty. Using data from the Bordeaux wine region from 1920 to 2009, it is shown that this model statistically outperforms the previously used constant regression models: a period characterized by strong effects of temperature on wine quality up to the mid-1960s was followed by an abrupt and steady decline to present marginal temperature effects. This pattern can be explained by key adaptive shifts implemented in the Bordeaux wine industry from the 1960s onwards, which likely dampened the relative impact of temperature on the inter-annual variability of wine quality. Additionally, estimated optimum growing-season temperatures are higher and more uncertain than previously modeled. These results suggest that previous approaches likely overestimated the effects of growing-season temperatures on Bordeaux wine quality during recent years. Consequently, the projected effects of future climate change on viticulture might be biased in this region.

KEY WORDS: Bayesian analysis · Climate change · Grapevine · Growing-season temperature · Hamiltonian Monte Carlo · Observation error · Time-varying coefficients · Viticulture · Wine quality rating

1. INTRODUCTION

Winemaking is one of the oldest agricultural activities, and is also one of the human enterprises most closely tied to the natural environment (Unwin 2005, White et al. 2009). The wine style of a certain area is the result of decades of grape variety selection in a fixed soil type under a baseline climate, the so-called *terroir* (van Leeuwen et al. 2004, White et al. 2009, Dougherty 2012). However, the inter-annual variability of wine quality is mainly the result of short-term climate variability, in particular the average temperature during the winegrape growing season. Recent studies have exploited this fact to explore the effects of short-term weather fluctuations on the inter-annual variability of winegrapes and wine quality at global (Jones et al. 2005), regional (e.g. Ashenfelter et al. 1995, Nemani

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et al. 2001, Storchmann 2005) and local scales (Chevet et al. 2011). Other approaches aim at characterizing the fine-scale structure of climatic conditions within wine regions in order to determine the suitability of different grape varieties (e.g. Hall & Jones 2010, Santos et al. 2012). In either case, the emergent consensus is that current climatic fluctuations have a large impact on the multiple dimensions of wine-making, from the organoleptic properties of the grapes to wine quality and prices (Mira de Orduña 2010).

The rising quality of world wines during the last decades has generally been attributed to the observed increase in surface temperatures in most wine regions (Jones et al. 2005). Hence, given the predicted increase in future planetary temperatures (IPCC 2013), research on the projected effects of a warming climate on viticulture has seen an upsurge in recent years (White et al. 2006, Hannah et al. 2013, Moriondo et al. 2013), paralleled by an exponential increase in the global surface of planted vineyards (Viers et al. 2013). The available projections of future spatial shifts in suitability for winegrowing (Hannah et al. 2013, Moriondo et al. 2013) rely on grapevine maturity groupings (e.g. Jones 2006). These groupings specify the optimum growing-season temperatures for each grape variety, and are ultimately based on observed phenological requirements and on the modeled impacts of climate fluctuations on wine quality (Jones et al. 2005). However, the reliability of this index has recently been questioned, as the average growing-season temperatures of many of the wine regions are currently above the ranges predicted by available maturity groupings, with no observed negative impacts on wine quality (van Leeuwen et al. 2013). Although a major effect of growing-season temperatures on inter-annual variability in wine quality is currently clear (e.g. Baciocco et al. 2014), some wine experts (e.g. Parker 2003) question the main role currently attributed to climate in explaining the rising quality of world wines, and identify the adaptive technological revolution experienced in key wine regions during the last 50 yr as the main factor explaining this increasing trend (Bisson et al. 2002, Paul 2002, Unwin 2005). Here, adaptation refers to the set of inter-related human factors that potentially modify the relative effect of climate on wine quality fluctuations through time, such as agricultural innovations in the vineyard, technological improvements in the cellar and increased reactivity of the winemakers to changes in expert and consumer preferences for certain wine styles (e.g. Bisson et al. 2002, Paul 2002, Parker 2003, Unwin 2005, Alston et al. 2011). Most of the available analyses on the long-term impact of climate on winemaking largely ignore the role that increasing adaptation may have in modulating weather impacts on wine quality (but see Haeger & Storchmann 2006, Alston et al. 2011), an approach termed the 'dumb farmer scenario' (Mendelsohn et al. 1994). The reason might be that deriving a quantitative measure accounting for the impact of adaptation on the weather/agriculture interface is far from straightforward (Haeger & Storchmann 2006, Alston et al. 2011), but the available historical narrative in fact provides a powerful proxy for expected cut-points and trends in the relative effects of climate on agriculture evolution (see Lamb 1995). In other words, although time-series analyses are fundamentally pattern-oriented, historical adaptations may provide mechanistic clues for explaining these patterns. In order to explore the hypothesis of an increasing role of adaptations on the temporal shift in wine quality fluctuations, we have formulated a key set of specific questions. (1) Has the effect of climate on wine quality varied in strength across time? (2) If so, in which direction and by what amount has it changed? (3) Can adaptations of the wine industry explain this pattern?

Here, a time-varying coefficient modeling approach (Hastie & Tibshirani 1993) is developed to address these questions in the evolution of wine quality in Bordeaux, the most important wine region in the world, throughout nearly a century. Through this novel modeling scheme it is possible to partition the temporal effects of temperature on wine quality across sequential winegrape growing seasons. Numerous studies have previously explored the relationships among Bordeaux growing-season weather, wine quality and prices (e.g. Jones & Davis 2000, Lecocq & Visser 2006, Ashenfelter 2008), and the historical evolution of viticulture within this region is very well documented (Paul 2002, Parker 2003, Unwin 2005). In particular, a profound technological revolution in both vineyard and cellar management took place in this area from the 1960s onwards (Paul 2002), and some authors have recently suggested that the relative impact of climate on winemaking in Bordeaux might have changed as a consequence (Chevet et al. 2011). Therefore, a specific prediction of the adaptation hypothesis is a structural shift in the effects of growing-season temperature on wine quality during the second half of the twentieth century, with progressively weaker effects of temperature across time. These results would have major implications for predicting the effects of future climate change on winemaking in this area.

2. DATA AND METHODS

2.1. Wine quality and climate data

Wine quality can be defined as the average rating assigned by wine experts to a vintage. Alternatively, economists regard quality as the willingness-to-pay, which is equivalent to the wine's auction price. The relationship between wine quality, vintage ratings and prices is nevertheless rather complex for 2 main reasons. Firstly, quality rankings by wine expert raters can have disproportionate effects on prices (Landon & Smith 1997, Jones & Storchmann 2001, Nemani et al. 2001, Roberts & Reagans 2007), but the opposite does not commonly apply (Hadj Ali et al. 2008). And secondly, given that the Bordeaux wine market is currently an income stabilization agricultural system, the prices of young wines are inversely related to quantity and hence largely decoupled from quality (Ashenfelter 2008). For these reasons, and given that consistent and reliable data on Bordeaux wine prices have not been readily available for the last century, vintage ratings by wine experts will be used here as surrogates for wine quality (e.g. Jones et al. 2005, Storchmann 2005, Roberts & Reagans 2007). Long-term data on red wine quality ratings comes from Tastet & Lawton (www.tastet-lawton.com), the oldest courtier firm in Bordeaux (Parker 2003). Although vintage assessments from this firm are available from 1795, only data for the modern and contemporaneous era (1920 to 2009) were used. Vintage ratings are made on a numerical scale, bound between 0 (worst quality) and 20 (highest quality), although a rating of 0 has never been given (Fig. 1a). This time-series is highly correlated with alternative vintage ratings used by other authors (see Fig. 1b and Section S3, Tables S1–S3 in Supplement 1 at www.int-res.com/articles/suppl/c064p187_supp/) and offers the advantage of being one of the longest available datasets for Bordeaux. In any case, the results presented in this study are independent of the time-series of wine quality ratings used.

Climatic data were obtained at the Bordeaux Airport, located in Mérignac (44° 49′ 54″ N, 0° 40′ 30″ E; see Fig. S1 in Supplement 1). Daily temperature data from 1920 to 2009 were gathered from the European Climate Assessment & Dataset project (Klein Tank et al. 2002), a team from the Royal Netherlands Meteorological Institute (KNMI; http://climexp.knmi.nl/). Given that this station is located within the Bordeaux city area, it might be affected by the Urban Heat Island effect (Kalnay & Cai 2003). To control for this, data for this weather station covering the period 1951 to 2009 were downloaded from the Global Historical Climatological Network (GHCN; www.ncdc.noaa.gov/ghcnm/v3.php). This dataset was homogenized using the pairwise correlation method of Menne & Williams (2009), which removes trends in temperature induced by changes in local land use and increasing urbaniza-

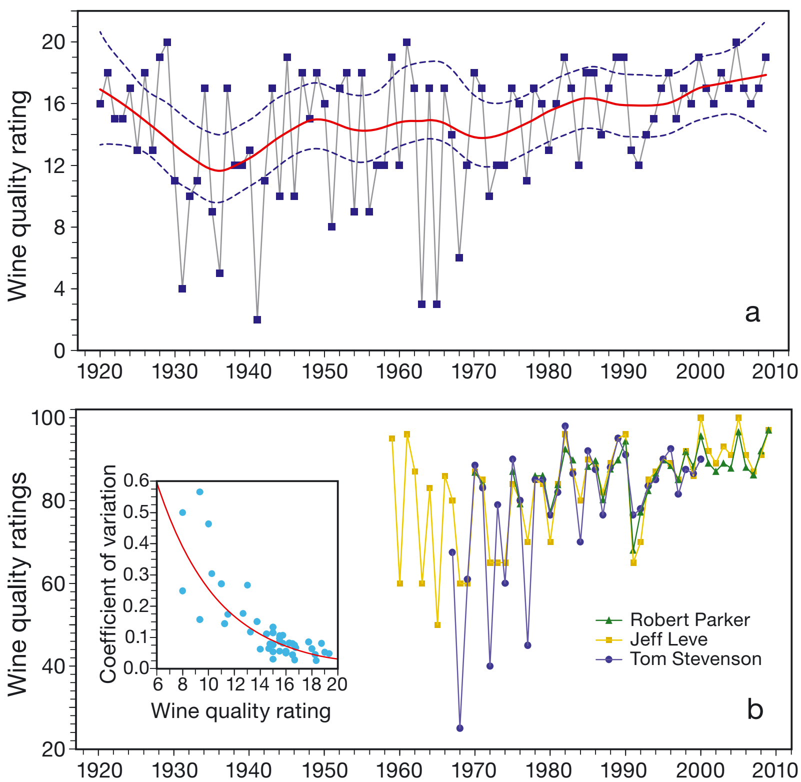

Fig. 1. Time-series of wine quality ratings for Bordeaux red wines. (a) The Tastet & Lawton series of vintage ratings is shown for the period from 1920 to 2009 (blue squares). To enhance multiannual fluctuations, a LOESS (locally weighted scatter-plot smoother) function with a smoothing parameter of 0.2 (red line) was fitted to the observed vintage rating time-series. Dashed blue lines around the trend show the 95 % confidence interval of the estimated function, obtained through 10 000 bootstrap replications of the original data. (b) Vintage quality ratings from 3 key wine experts: Robert Parker (1970 to 2009, green triangles), Jeff Leve (1959 to 2009, yellow squares) and Tom Stevenson (1967 to 2009, blue circles). The rating scales for Robert Parker's and Jeff Leve's time-series are 50 to 100, for Tom Stevenson's this scale is 0 to 100. The inset shows an exponential function fitted to the regression of the coefficient of variation of the ensemble of annual wine ratings on the averaged rating obtained from the 4 sources shown, after rescaling all the time-series to a 0 to 20 scale

tion, among other biases. The final temperature dataset used was thus reconstructed by merging the original time-series from the KNMI (1920 to 1950) and the homogenized data from the GHCN (1951 to 2009). This dataset is a homogenized update to the gridded temperature dataset used by Jones et al. (2005) (see Fig. S2 in Supplement 1). The reliability of this dataset was validated using 11 alternative weather stations located within the Bordeaux wine area (see Section S1 and Figs. S1 to S4 in Supplement 1). The average date of grape harvesting within the Bordeaux wine area during the study period was 22 September (Daux et al. 2012), so temperature data were averaged from April to September to derive a time-series of growing-season temperatures (Fig. 2a). The number of days in which the average temperature exceeded 30°C, as well as the average temperature of these days, was also derived (Fig. 2b–c).

2.2. Modeling time-varying effects of climate on wine quality

Previous studies on the effects of climate on wine quality (e.g. Ashenfelter et al. 1995, Jones et al. 2005, Storchmann 2005, Webb et al. 2008) have used a multiple regression model, sometimes called an econometric model (Jones & Storchmann 2001), where yearly wine quality ratings are regressed on growing-season temperatures through linear and possibly quadratic effects. This model takes the general form:

$$WR_t = I + \alpha Y_t + \beta_l T_t + \beta_q T_t^2 + \varepsilon_t \qquad (1)$$

where WR_t stands for the wine quality rating in year t, Y_t stands for year t, T_t and T_t^2 stand for the linear and quadratic growing-season temperatures in year t, I is the intercept, α is the temporal trend of the wine quality series and β_l and β_q represent the linear and quadratic effects of temperature, respectively. The term ε_t stands for stochastic external effects, arising from a set of independent and identically distributed (i.i.d.) random variables following a normal distribution of mean 0 and process variance σ^2, $\varepsilon_t \sim N(0, \sigma^2)$.

An implicit assumption of the standard econometric model, hereafter the constant model, is that the effect of growing-season temperature on wine quality is stationary, that is, there is no long-term temporal variability in the climatic control of vintage quality. This assumption can be relaxed in a straightforward manner through the use of a time-varying coefficients (hereafter, TVC) specification (Hastie & Tibshirani 1993). The model in Eq. (1) would now be rewritten as:

$$WR_t = \alpha_t + \beta_{l,t} T_t + \beta_{q,t} T_t^2 + \varepsilon_t \qquad (2)$$

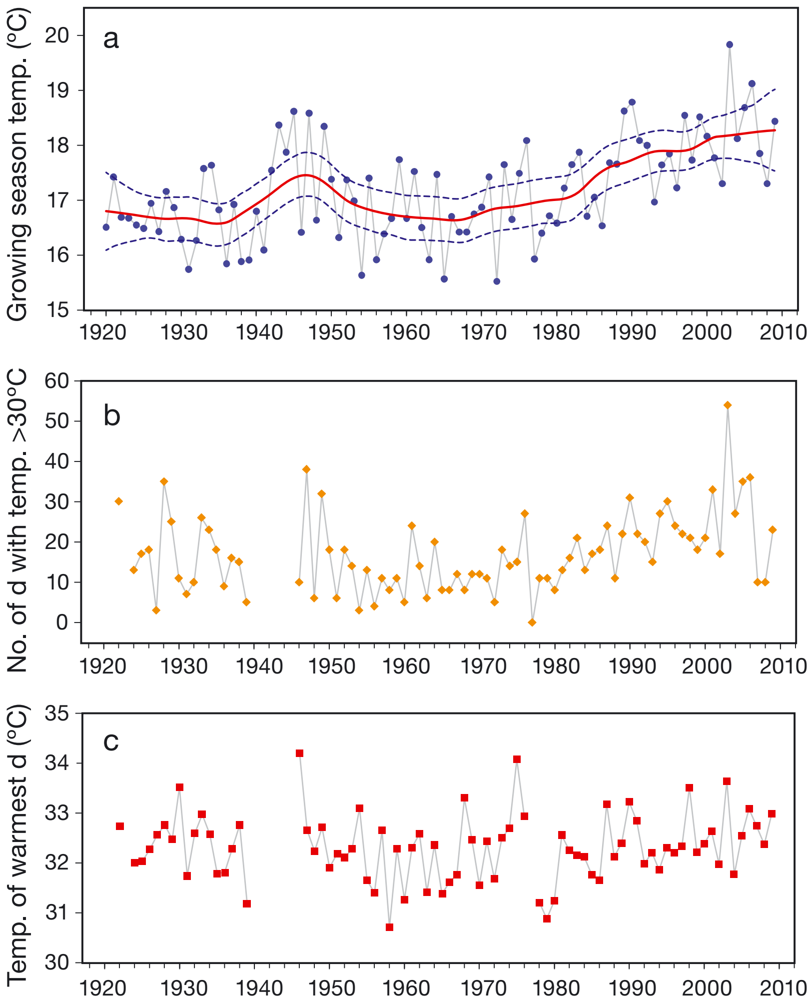

Fig. 2. Climatic fluctuations in Bordeaux, France, from 1920 to 2009. (a) Time-series for the temporal evolution of homogenized winegrape growing-season temperatures, averaged from April to September (blue dots). To enhance multi-annual fluctuations a LOESS function with a smoothing parameter of 0.2 (red line) was fitted to the observed temperature time-series. Dashed blue lines around the trend show the 95% confidence interval of the estimated function, obtained through 10 000 bootstrap replications of the original data. (b) The number of days in which the temperature was >30°C during each growing season (orange diamonds). (c) The average temperature (°C) of these days (red squares)

where the coefficients α_t, $\beta_{l,t}$, $\beta_{q,t}$ and σ_t now evolve through time according to a given function. In principle, any function can be specified for the time-varying coefficients, such as a simple random walk, an autoregressive model, or more complex functional specifications (see Hastie & Tibshirani 1993, Fan & Zhang 2000). Given that no previous information is available, a simple random walk with drift was used to provide the most parsimonious fit (e.g. West & Harrison 1997, Primiceri 2005). Specifically, the location coefficients α_t, $\beta_{l,t}$, and $\beta_{q,t}$ were modeled as:

$$\begin{aligned} \alpha_t &= l_\alpha + \alpha_{t-1} + \varepsilon_{\alpha,t} \\ \beta_{l,t} &= l_{\beta_l} + \beta_{l,t-1} + \varepsilon_{\beta_l,t} \\ \beta_{q,t} &= l_{\beta_q} + \beta_{q,t-1} + \varepsilon_{\beta_{q,t}} \end{aligned} \qquad (3)$$

where parameter l_x (x stands for α, β_l, or β_q) is the diffusion (drift) coefficient of the random walk for each time-varying coefficient, and ε_t stands for i.i.d. noise with 0 mean and coefficient process variance ρ_x^2. The random walk for the coefficient α_t now models the time-varying, locally linear trend of the wine quality time-series through changes in model intercepts. Given the trends in wine ratings and temperature, the variable Year does not appear here explicitly because this made convergence to a posterior distribution less efficient. Hence, the TVC specification can model the time evolution of the effect of temperature on wine quality across sequential growing seasons ($\beta_{l,t}$ and $\beta_{q,t}$), along with the time-varying trend in wine quality not accounted for by temperature (α_t). The scale parameter σ_t, accounting for the time-varying process standard deviation in wine quality ratings, was also modeled as a linear random walk with drift such that:

$$\sigma_t = l_\sigma + \sigma_{t-1} + \varepsilon_{\sigma,t} \qquad (4)$$

where the parameter l_σ is the drift coefficient, and $\varepsilon_{\sigma,t}$ stand for i.i.d. noise with 0 mean and process variance ρ_σ^2. This equation models the stochastic volatility of wine ratings, which makes the developed TVC model analogous to the conditional heteroscedastic models commonly used in econometric approaches (West & Harrison 1997). This is convenient because the time-series of wine quality ratings displayed reduced variance across time (see 'Results'). Finally, a time-varying estimate for the optimum growing-season temperature can be obtained by setting to 0 the partial derivative of wine quality with respect to temperature (see Jones et al. 2005).

2.3. Accounting for uncertainty in wine quality ratings

Although wine expert ratings are fundamentally subjective (Ashenfelter & Jones 2013), they are related to certain sensory characteristics of the wine that reflect objective factors (Bisson et al. 2002), so the cross-correlation between different sets of expert ratings is usually very large (e.g. Jones et al. 2005, Cardebat & Figuet 2013, Baciocco et al. 2014; see Table S3 in Supplement 1). However, it is also known that wine experts show low consistency in the ratings of the same wines among rating sessions (e.g. Gawel & Godden 2008, Hodgson 2009). This has led some authors to suggest using combined ratings by a small set of experts, which generally increases the consistency of wine quality assessments (Gawel & Godden 2008). To date, no attempt has been made to account for this rating uncertainty in the analyses of the long-term climatic effects on wine quality. Here, an observation model accounting for this uncertainty will be considered, of the form:

$$WR_{\text{obs},t} \mid WR_t \sim N(WR_t, \tau_t^2) \qquad (5)$$

where $WR_{\text{obs},t}$ denotes the rating assigned by Tastet & Lawton for each vintage and year t (Fig. 1a). This observation is conditioned upon a latent (unobserved) vintage rating, WR_t (Eqs. 1 & 2) that represents the consensus that would be obtained from a set of an asymptotically large number of expert raters. Hence, the observed rating for each year is regarded as emerging from a normal distribution with the latent vintage rating as the mean and an observation rating variance of τ_t^2. A fundamental problem in time-series analysis is the estimation of this variance (West & Harrison 1997). Here, a time-varying estimate for τ_t^2 will be approximated from a set of alternative wine quality ratings from 3 highly reputed wine experts (Fig. 1b; see Section S3 and Table S3 in Supplement 1 for further details). Additionally, an alternative model will be fitted accounting for within-season variance in growing-season temperatures (see Section S2 and Fig. S5 in Supplement 1).

2.4. Estimation of parameters and model adequacy

Parameter estimation (Eqs. 1–5) was performed through Bayesian Markov Chain Monte Carlo integration using Hamiltonian Monte Carlo (HMC; Neal 2011, Gelman et al. 2013). In contrast to other commonly used simulation schemes, this method uses physical system dynamics to derive future states in the Markov chain, and not a probability distribution.

This algorithm is thus much more efficient, and the convergence to a stationary posterior distribution is much faster (see Section S4 in Supplement 1). Note that the constant model in Eq. (1) is a nested case of the TVC model (Eqs. 2–4), where the process variances ρ^2 and the drift coefficients I_x are set to 0, and the coefficient α is specified as constant. The recently developed Watanabe/Akaike (or widely applicable), information criterion (WAIC; Watanabe 2010) will be used to compare the performance of both models in terms of out-of-sample predictive fit (see Section S4 in Supplement 1). Models minimizing this quantity provide a better posterior predictive fit. Posterior predictive checks (Gelman et al. 2013) were conducted through the correlation of the observed time-series of vintage ratings to an ensemble of time-series of vintage ratings simulated from the posterior parameter and latent rating values. The constant and TVC models were written in the Stan C++ language (Stan Development Team 2014), which uses the No-U-Turn algorithm for implementing HMC integration (Hoffman & Gelman 2013). Further details on model specification, along with the dataset and the RStan code used to produce the results of this paper are given in Table S1 and Section S4 of Supplement 1 and in Supplement 2 at www.int-res.com/articles/suppl/c064p187_supp/.

2.5. Evaluating the performance of the TVC model through numerical experiments

Previous fits of the econometric model to world wine quality data suggest a general pattern of negative quadratic effects of temperature on vintage ratings (Jones et al. 2005). This suggests that, for most wine areas, the optimum temperature for producing wines of the highest quality is actually very close to the currently observed values. Given that in many wine areas growing-season temperatures have been rising steadily for the past few decades (Jones et al. 2005), this raises the possibility that a TVC model could detect a shrinking temporal effect of temperature on wine quality even if no genuine statistical decoupling of both variables should exist. This might be due to the bounded nature of the vintage quality data: yearly vintage ratings have been very close to optimum in recent times, so this reduced temporal variance would shrink the local regression parameters to 0 even if the absolute effect of temperature on wine quality were not to change. To rule out this possibility, 2 further analyses were conducted. Firstly, the TVC model was fitted to the detrended time-series of wine quality ratings and growing-season temperatures to check whether the observed temporal trend towards higher growing-season temperatures might be artificially shrinking the variance in wine quality ratings. Secondly, a more robust numerical experiment was designed. The posterior parameter estimates of the constant and TVC models coupled to the original temperature data were used to derive an ensemble of 30 synthetic time-series of vintage ratings from each fitted model; these time-series were truncated to a 0 to 20 scale, as were the original Taste & Lawton data. The TVC model (Eqs. 2–5) was then fitted to each of these truncated, synthetic time-series using the same procedure as above, and the plots of the time-varying coefficients were compared to the original values used to generate the synthetic data. If the reduced temporal variance of vintage ratings during recent times is artificially shrinking the local regression parameters to 0, the TVC model fitted to the synthetic ensemble would recover a time-varying pattern in the effects of temperature on wine quality even if the underlying model generating the data is a constant one (Eq. 1). However, if the TVC model successfully recovers the original dynamics of both a constant model and a TVC model, this would suggest a genuine statistical decoupling of wine quality from temperature.

3. RESULTS

3.1. Temporal trends in wine quality and climate

Fig. 1a depicts the temporal evolution of Bordeaux wine quality according to Tastet & Lawton's ratings from 1920 to 2009. A weak trend towards higher quality wines was detected through time (Spearman's rank-oder correlation, $r_S = 0.26$, 10 000 bootstrapped p-value, $p_{boot} = 0.01$). Fig. 2a shows the temporal evolution of the merged growing-season temperatures during the last 9 decades. A consistent temporal trend towards warmer temperatures was also evident in Bordeaux ($r_S = 0.49$, $p_{boot} = 0.0001$). This general trend was also apparent in the time-series for the number of days with average temperature >30°C during each growing season (warmest years; Fig. 2b): 2003 and 1947 were the years with the higher number of warm days. However, the years with the highest average temperatures were 1946 and 1975 (Fig. 2c).

3.2. TVC regression of wine quality on temperature: model fitting and adequacy

Fig. 3 shows the plots of the time-varying coefficients assessing the fluctuating effects of growing-

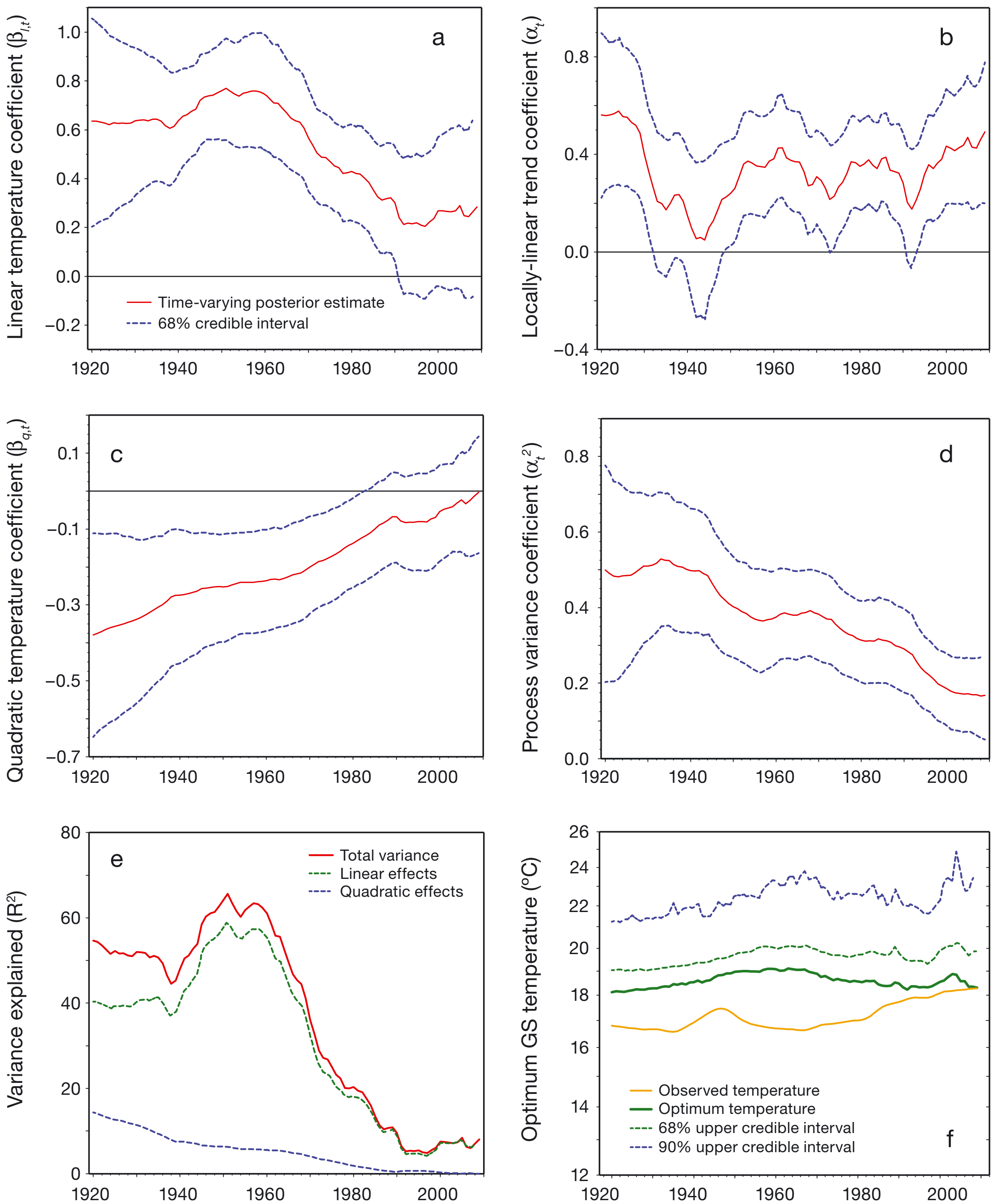

Fig. 3. Time-series of Bayesian posterior estimates for the time-varying coefficients model relating temperature fluctuations to wine quality in Bordeaux from 1920 to 2009. (a) The linear time-varying effect of temperature on wine quality, (b) the locally linear trend , (c) the quadratic time-varying effect and (d) the time-varying process variance. In all panels, the posterior estimates for the time-varying effects are depicted with a red line, while the dotted blue lines stand for the 68% credible intervals for each posterior estimate. (e)The time-varying proportion of variance (R^2) in wine quality explained by temperature, for linear (green dotted line) and quadratic (blue dotted lines) effects, and their summed effects (thick red line). (f) Solid green line: posterior estimates for the time-varying optimum growing-season (GS) temperatures (°C); green and blue dotted lines: 68 and 90% upper credible intervals for the estimates, respectively. For comparison, the observed temperature trend obtained with a smoothing LOESS function (see Fig. 1) is shown as a solid yellow line. Note the logarithmic scale of the temperature axis

season temperature on wine quality from 1920 to 2009. The linear temperature effect displayed a clear shift in this effect during the mid-1960s (Fig. 3a): prior to this period, wine quality was under strong climatic control (average $\beta_{l,t}$ = 0.680). After this period, however, an exponential decline towards marginal values became evident (average $\beta_{l,t}$ since year 2000 = 0.267). This pattern was largely mimicked by the quadratic temperature effect (Fig. 3c), since large non-linear effects of temperature during the first decades monotonically approached 0 towards the end of the series. These shifts amounted to an 8-fold decline in the temporal effect of temperature on wine quality at the end of the time-series, as measured by the proportion of explained variance in wine quality fluctuations (R^2; Fig. 3e). Interestingly, the locally linear trend coefficient (Fig. 3b) did not display a constant temporal trend in wine quality ratings after controlling for the time-varying effects of temperature, and the time-varying process variance coefficient declined systematically through time (Fig. 3d). This suggests that the observed positive trend in wine quality ratings was most likely due to reduced temporal variance in ratings rather than to an increase in average vintage quality.

The posterior estimated time-varying optimum growing-season temperatures displayed a pattern of increasing estimation uncertainty across time (Fig. 3f); the time-averaged estimate of the optimum temperature for producing wines of the highest quality was >18.6°C (Table 1), but optimum temperatures >21°C are currently feasible with a large posterior probability (90%; Fig. 3f). Given that the time-varying quadratic temperature coefficients were close to 0 during recent times (Fig. 3c), these figures were highly conservative lower-bound estimates. Table 1 shows the parameter estimates of the fitted models. The fitting of the TVC model was better relative to the constant model, according to the smaller out-of-sample predictive fit index of the former (WAIC; Table 1).

Fig. 4 shows plots of the posterior predictive checks conducted with simulated time-series from the fitted TVC and constant models. The average correlation between the observed time-series of wine quality ratings and the set of simulated time-series was larger for the TVC model (0.58 ± 0.05, 1 SD) than for the constant model (0.48 ± 0.06). In the TVC model, most of the posterior simulated wine ratings tended to cluster around the $Y = X$ regression line, and only the extreme lower values were slightly biased (Fig. 4a). This was expected given the bounded nature of the wine quality rating scale. In contrast, for the constant model, the variability in many of the posterior simulations of the ratings was generally large and values tended to deviate from the $Y = X$ line to a greater extent (Fig. 4b). The fitting of the TVC model accounting for within-season temperature variability yielded qualitatively the same results relative to the original model shown here; moreover, the proportion of variance in wine quality explained by temperature increased by an average of 3.3% when the within-season variance was taken into account (see Fig. S5

Table 1. Posterior parameter estimates (±SD) for the constant and time-varying coefficients models assessing the effects of temperature on Bordeaux wine quality from 1920 to 2009, obtained through Bayesian Hamiltonian Monte Carlo integration. WAIC: Watanabe/Akaike information criterion

Parameter	Symbol	Model	
		Constant	Time-varying
Constant trend	α	0.009 ± 0.078	–
Drift of locally linear trend	I_α	–	−0.002 ± 0.018
Process variance of locally linear trend	ρ^2_α	–	0.020 ± 0.030
Linear temperature effect	β_l	0.607 ± 0.079	0.526 ± 0.128[a]
Drift of linear temperature effect	I_{β_l}	–	−0.004 ± 0.014
Process variance for linear temperature effect	$\rho^2_{\beta_l}$	–	0.011 ± 0.013
Quadratic temperature effect	β_q	−0.189 ± 0.052	−0.198 ± 0.103[a]
Drift of quadratic temperature effect	$I_{\beta q}$	–	0.004 ± 0.006
Process variance for quadratic temperature effect	$\rho^2_{\beta_q}$	–	0.002 ± 0.005
Process variance for wine rating evolution	σ^2	0.383 ± 0.063	0.367 ± 0.077[a]
Growing-season temperature optimum (°C)		18.767 ± 1.002	18.606 ± 0.294[a]
Variance in wine quality explained by temperature	R^2	0.413 ± 0.130	0.362 ± 0.216[a]
Out-of-sample predictive fit	WAIC	175.747 ± 13.190	170.857 ± 11.175
Effective number of parameters	P_{eff}	7.971 ± 1.382	22.117 ± 1.842

[a]Quantities for these parameters are time-averaged estimates, and are shown here only for comparison

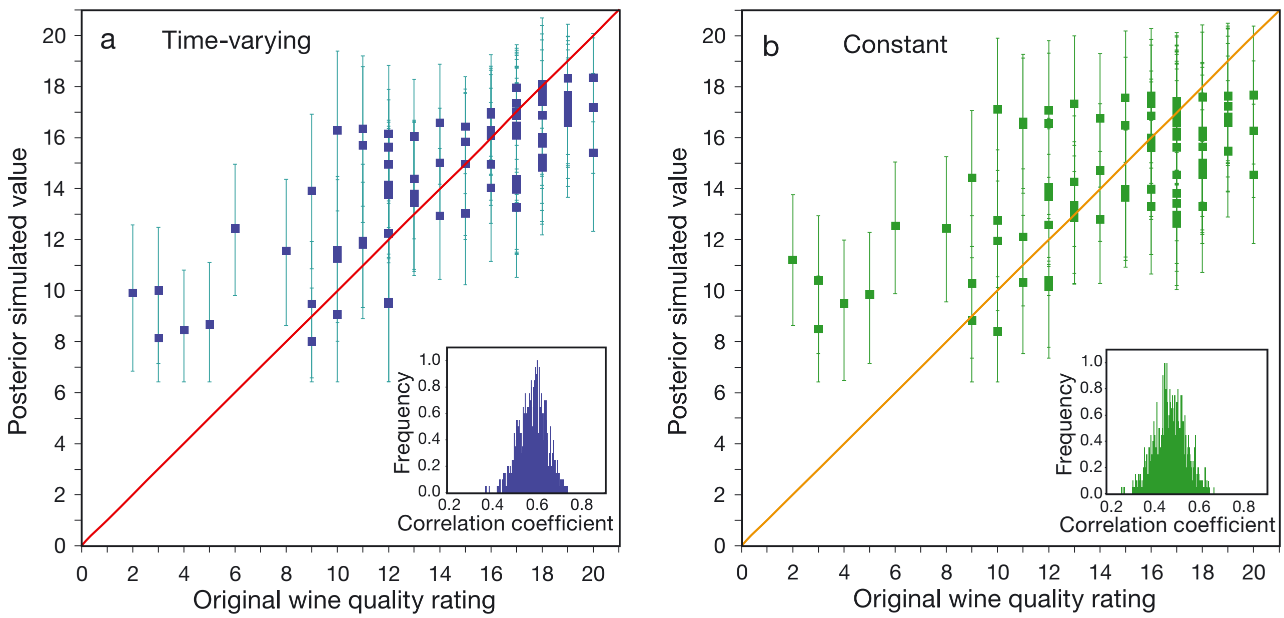

Fig. 4. Posterior predicted checks performed with (a) the time-varying coefficients model and (b) the constant regression model, assessing the effects of temperature fluctuations on Bordeaux wine quality from 1920 to 2009. For each panel, the average (squares) and standard deviations (whiskers) of 1000 posterior-simulated time-series of wine quality ratings generated from the fitted models are regressed against the original value. The diagonal line in each graph is the $Y = X$ regression line. The inset in each panel represents the frequency distribution of Pearson's product-moment correlations between the original time-series of wine quality ratings and each of the 1000 posterior-predicted time-series

in Supplement 1). Finally, model estimates were quite robust to even unrealistically large levels of wine rating uncertainty (Fig. S6 in Supplement 1).

3.3. Performance of the TVC model

The results of the fitting of the TVC model to the nonlinearly detrended time-series of growing-season temperatures and wine quality ratings yielded essentially the same results relative to the fitting of the model to the raw time-series (Fig. S7 in Supplement 1). Fig. 5 shows the results of the numerical experiments conducted with the TVC model. Even with as few as 30 simulated time-series, the TVC model was very successful in recovering the dynamics of the original model used to produce the synthetic data. The linear time-varying temperature coefficient suggested that the abrupt shift observed in the mid-1960s from a strong climatic control of wine quality to marginal values was robust enough to recover the dynamics (Fig. 5a), as was the drift in the quadratic coefficient (Fig. 5b). The posterior predictive estimation of the process variance was also successful, for both the TVC (Fig. 5c) and constant models (Fig. 5f). Remarkably, the TVC model was able to correctly identify as constant the average fitting to the ensemble of synthetic time-series emerging from a constant model, for both linear (Fig. 5d) and quadratic coefficients (Fig. 5e). These results suggest that the variance reduction in wine quality ratings during the last decades was larger than expected from warming temperatures alone. Thus, the modeled abrupt shift towards marginal temperature effects on wine quality (Fig. 3) was most likely due to a genuine gradual statistical decoupling of both variables, and not to a modelling artifact.

4. DISCUSSION

This study revealed that a model accounting for a time-varying effect of growing-season temperatures on Bordeaux wine quality provides a better fit than the previously used constant models (Jones et al. 2005). This finding is backed-up by numerical experiments, which suggest that the observed reduction in the inter-annual variability of Bordeaux wine quality is larger than expected from warming temperatures alone. An abrupt drop during the mid-1960s in the linear control of wine quality by growing-season temperatures was followed by an 8-fold decrease in predictability of wine quality fluctuations within a 30 yr period. Changes in the non-linear effects of temperature were largely monotonic, although a

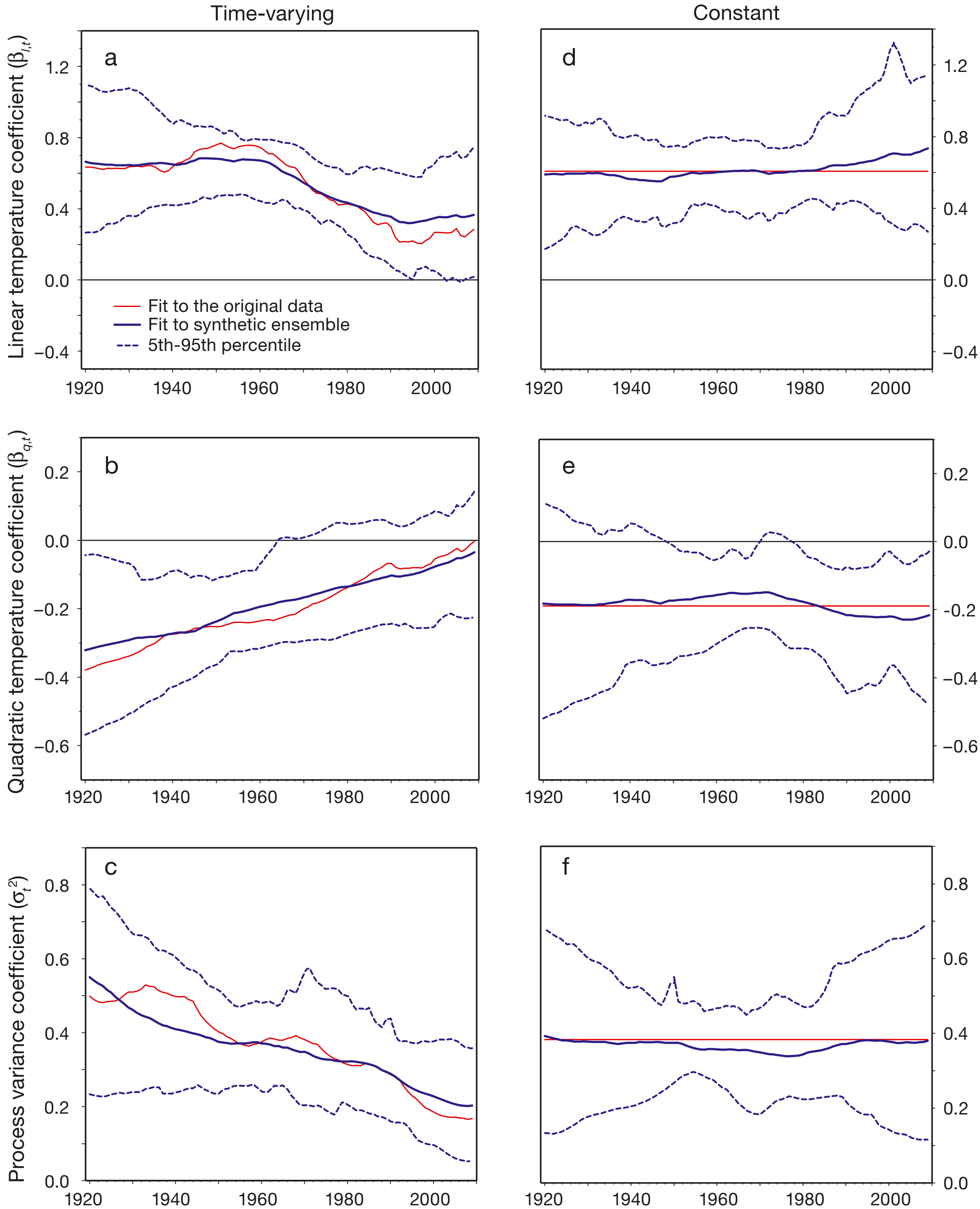

Fig. 5. Numerical experiments testing the ability of the time-varying coefficients (TVCs) model to recover the simulated dynamics from the fitted TVCs (a,b,c) and constant models (d,e,f). For each fitted model, 30 synthetic time-series were randomly drawn using the set of posterior parameter estimates of the original models (shown here as red lines) and the time-series of observed temperature trends. The TVC model was then individually fitted to each of these series, and the average posterior estimates of the ensemble of synthetic time-series are depicted as thick blue lines along with the 5 to 95 percentile bands (broken lines), equivalent to the 90% credible interval. (a–c) Experimental fit of the linear and quadratic TVCs along with the time-varying process variance to the simulated time-varying model, respectively. (d–f) Experimental fit of the linear and quadratic TVCs along with the time-varying process variance to the simulated constant model

locally accelerated change from strong quadratic effects to marginal values was also found in the mid-1960s. The average temperature of the warmest seasons during the last 90 yr did not display a temporal trend, and even the warmest seasons were found prior to the 1980s. Overall, it is highly unlikely that the structural change in the climatic control of Bordeaux wine quality across time is related to long-term shifts in growing-season climate. Rather, these results can be explained by a structural change in viticulture, as suggested by the adaptive hypothesis.

Fundamental changes in the world wine industry have taken place during the last decades, from technological shifts in the management of vineyards and the production of wines to changes in consumer preferences for certain wine styles (Bisson et al. 2002, Paul 2002, Unwin 2005, Alston et al. 2011). A particularly dramatic change was the generalized use of synthetic pesticides from the mid-1960s. This prevented some of the worst vine diseases, such as phylloxera or powdery mildew, from causing the massive damage that was common during the first half of the 20th century (see Gale 2011). Additionally, during the 1970s, the large-scale implementation of vine grafting with disease-resistant rootstocks and clones further decreased the effects of catastrophic weather and disease outbreaks (Paul 2002). Some other miscellaneous changes, such as vine pruning and crop thinning to decrease crop yields and increase wine quality, as well as the generalized implementation of computer-controlled fermentation and wine aging, took place from the 1960s onwards (Paul 2002, Parker 2003). Interestingly, Chevet et al. (2011) also found a shift in 1960 from large effects of temperature on yields to marginal values within a single wine state in Bordeaux, and attributed this structural change to the abovementioned factors . This pattern is consistent with those in other winemaking regions. For example, recent changes in sugar and acidity levels in California wine grapes, and hence in perceived wine quality, have been attributed to strategic marketing decisions from winemakers, and only secondarily to temperature during the growing season (Alston et al. 2011). Additionally, winemaking craftsmanship, and even brand reputation, may explain a large proportion of variation in the current prices of American Pinot Noir wines (Haeger & Storchmann 2006). The results of the present paper further suggest that future studies focused on the evolution of wine quality might benefit from exploring the potential time-varying effects of climate. Moreover, the explicit modeling of within-season temperature variability improved model estimation for Bordeaux wine quality evolution, which suggests a novel approach for increasing predictability in wine quality.

Global coupled models of future climatic dynamics predict an average temperature increase of 2°C during the winegrape growing season by 2050 for many wine regions in Europe (IPCC 2013, Moriondo et al. 2013). These results are in agreement with the projected shifts in agroclimatic conditions in Europe, which predict higher drought stress, increases in average temperatures and a shortening of the active growing season (Trnka et al. 2011). In general, the predicted changes for viticulture include a poleward displacement of most of the wine regions to new areas and a decrease in suitability of most of the current regions. For example, Moriondo et al. (2013) predicted an average of 60 % decrease in the suitable area for winegrowing in Bordeaux by 2020, and even more severe decreases in other regions. These results are in agreement with data by Hannah et al. (2013), which further suggest that the planetary shifts projected for wine regions might have severe negative impacts on environmental conservation (Viers et al. 2013). A key assumption of these approaches is that the empirical information used to derive the projected effects of climate change actually reflect the optimum conditions for grape growing, in particular the current bioclimatic zoning of wine regions (e.g. Santos et al. 2012) and grapevine maturity groupings (Jones 2006). The results of the present paper suggest, however, that previous estimates for optimum growing-season temperatures in Bordeaux (17.4°C; Jones et al. 2005) have been underestimated. A temperature range of 20 to 22°C, which is larger than the values predicted by the worst-case emission scenario for 2050 (IPCC 2013), might include optimum temperatures for producing high-quality wines in Bordeaux, as suggested by the TVC model. Although accurate estimation of these values is far from trivial, these results agree with the observation made by van Leeuwen et al. (2013) for some of the wine regions in the world, suggesting that available maturity groupings may previously have underestimated the upper values of the range of optimum temperatures.

In conclusion, the present study posits that the adaptive shifts evidenced during the last decades in the Bordeaux wine industry likely dampened the relative impact of climatic variability on wine quality by shrinking its inter-annual variability. This suggests that the effects of current growing-season temperatures on wine quality have been overestimated in this region. Given that these estimates usually provide the baseline for projecting the effects of future climate change on viticulture, the present results show that these projections might be biased for Bordeaux. However, caution should be taken. Although in the absence of physiological modeling it is difficult to assess the potential effects of changing climates on grape chemistry (van Leeuwen et al. 2013), ripening is indeed highly sensitive to exceedingly warm temperatures, as they can disrupt the balance between sugar and acidity levels and the quality and aging potential of wines (Mira de Orduña 2010). In the future, a persistent warming trend in growing-season temperatures might force winemakers to implement further adaptive changes in order to maintain high-quality vintages, such as shifting to grape varieties better adapted to warmer climates or even re-locating vines to more northern latitudes (e.g. Hannah et al. 2013). Moreover, the predicted increase in the frequency of extreme climatic events at mid-latitudes, such as heat waves, droughts and floods (Meehl & Tebaldi 2004, Schär et al. 2004, White et al. 2006, IPCC 2013) may have dramatic effects on the production and quality of single vintages not accounted for by the time-varying effects of temperature on wine, irrespective of its local magnitude.

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