The 6th International Conference on Economic Management and Green Development (ICEMGD 2022)
DOI: 10.54254/2754-1169/3/2022827

Correlation Between Stock Returns of Wine Corporations and Weather Conditions

Yijie Li[1,a,*], Wen Xin[2]

[1]*University of Washington, Seattle WA 98195-4550, USA*
[2]*South China Normal University, PanYu District, Guangzhou City, Guangdong Province, PRC*
a. yijie666@uw.edu
**corresponding author*

Abstract: Among determinants of wine spot prices, the weather is one of the most influential factors. Previous studies have confirmed the spot price of fine wine is corre-lated with some weather variables, such as the air temperature. Also, much re-search illustrates some weather conditions are related to the stock market. In this paper, we focus on the correlation between some weather variables as main de-terminants of wine prices and the stock returns of wine companies which are listed on NYSE. We have several conclusions: (1) return of equity of wine com-panies has a negative correlation with the level of precipitation; (2) results are more significant when controlling years; (3) the level of precipitation has greater negative impact on returns during planting season of grapes; (4) the odds of hav-ing positive returns in planting season is lower than non-planting season.

Keywords: Wine Economics, Stock Returns, Econometrics.

1. Introduction

The wine market has contributed approximately 220 billion dollars to United States economy in 2017, according to Wine America. Obviously, fine wines have a huge impact on the United States. Despite some features of agricultural commodities, fine wine can be preserved as an investment, motivating many investors and economists to study the spot pricing of wine.

Early research works have started to exhibit evidence that weather could influence wine pricing since 1990s. Jones and Storchmann [2] summarize four characteristics to assess wine market prices, which are how climate alters grape composition, difference of grape composition, quality evaluations of wine, and effects of aging. Concretely, the dry weather condition with higher air temperature is associated with higher spot prices of fine wines [7]. A study based on Australian context has the same conclusion, illustrating both rainfall and extreme temperature affect the wines (Cabernet Sauvignon, Merlot, Chardonnay, and Sauvignon Blanc) significantly [8].

The majority of wine-related research focuses on the price and quality of wine. Since wine can be considered as either common commodities or an investment in the form of futures, wine industry can be studied in different directions. In addition to wine market prices, the weather factors also correlate with the stock return. Hirshleifer and Shumway [9] examine the relationship between the sunlight and stock index returns across 26 cities. They find that sunshine has a positive correlation with daily stock returns, but other factors, like snow and rainfall, are not related to returns.

DOI: 10.54254/2754-1169/3/2022827

Unlike previous studies of weather determinants of wine market prices and relationship between stock returns and weather, our research will highlight the impact of weather on stock returns of wine companies in a monthly period.

In this paper, section 2 is an overview of previous literatures, helping elicit our research goals. Section 3 will introduce the data we collected and models. The results and interpretations are described in section 4. Finally, the last section is a conclusion and some discussions of this paper.

2. Literature Reviews

In microeconomic domain, several studies have investigated the correlation between the wine prices in the money market and potential factors. Early publications in an econometric assessment of fine wine pricing have shown that higher temperatures, especially in summer, could cause wines to become more valuable since dry weather conditions contribute to higher sugar level and lower acid level of the grape during vintage, which result in a better quality of fine wines [2]. Jones and Storchmann [2] also illustrate the retail prices of wines are responsive to maturity level as well as wine evaluation indicator (Parker-point ratings), and both are positively associated with wine market prices. Concretely, aging wines are scarce in the market so relatively high prices are always related to aging wines [2].

Earlier research might ignore some correlations between predictor variables, so some subsequent studies control independent variables to reduce effects from collinearity. In [3], the origin of wine production exhibits a significant impact on price level of fine wine under controlling all other determinants. If we choose a specific region in the North American wine market as a baseline, fine wines that come from France are sensitive to prices and can be sold at a premium, whereas others coming from other countries have almost no difference in price level [3]. A recent study examines the impact of different trading venues on wine prices; the characteristics of Bordeaux fine wines have various responses to affect transaction prices across three trading venues, which are auctions, electronic exchange market, and the OTC market [5].

Wines are also analyzed in the macroeconomic environment. A study [5], for example, sheds light on macroeconomic factors of wine market pricing, such as real interest rates, the money supply, and the proportion of investment funds in GDP. Except for commodities in the industry, wines unfold many attributes of an investment. In the capital market, some investors choose to put fine wines in their portfolio for earning benefits or hedging a few risky financial assets. Storchmann [1] concludes that, based on previous research, wines can generate gains above average and outperform Treasury bills on the rate of returns.

Collectively, there has been substantial research on how climate issues and other factors influence the wine market prices. Apart from wine pricing, weather as the main determinants of wine prices may also affect stock market of companies that are related wines. Many psychology literatures investigate weather impact upon the state of mind to a great extent, and the mood will directly affect decision-making and trading behavior during exchanges. Hirshleifer and Shumway [9] have established that sunshine coverage has a significant correlation with daily stock returns, i.e., the sunnier the exchange is located, the higher the daily return of the stock index, meanwhile, other weather conditions show they are unrelated to stock returns, such as rain and snow. On the contrary, Loughran and Schultz [11] illustrate cloudy weather conditions of a company's headquarter is unrelated its stock return. Furthermore, Floros [10] examines that the temperature has a negative effect on stock index return from Lisbon Stock Exchange (PSI 20).

Unfortunately, one of the limitations of literatures mentioned above is that the weather at exchange venues and the weather in which investors are while making exchanges are probably not the same. This paper will focus on wine corporations that are listed in NYSE (New York Stock Exchange). Instead of researching weather collected from making exchange orders, we aim to study whether

DOI: 10.54254/2754-1169/3/2022827

stock returns of wine companies depend on weather data exacted from origin of fine wines, such as the chateau company runs.

3. Methodology

In section 3.1, we will explain the source of data and define variables for research goals. Section 3.2 fits the least-squares regression and section 3.3 uses logistic regression. Moreover, we estimate response variable by different fixed effect model in section 3.4 and adopt interaction terms in 3.5.

3.1. The Data and Variable Constructions

In this section, the data is retrieved from two main sources for this paper. First, we acquire daily security Compustat data for sample wine companies chosen from 2010 to 2019 provided by WRDS (Wharton Research Data Services). All companies are NYSE-listed. Three attributes of security daily Compustat data are fetched to compute stock returns at a monthly period, which are PRCCD (daily closing market price), AJEXDI (daily adjustment factor), and TRFD (daily return factor). First step to calculate stock return is to adjust the daily security price by dividing closing price by daily adjustment factor, and then multiply the total return factor. Finally, we divided value of the last day in a period by that of the first day in a period to compute stock return. Therefore, stock return is calculated as:

$$R_{m,t} = \left(\frac{\left({}^{PRCCD_{eom,t}}/_{AJEXDI_{eom,t}} \right) \times TRFD_{eom,t}}{\left({}^{PRCCD_{m0,t}}/_{AJEXDI_{m0,t}} \right) \times TRFD_{m0,t}} - 1 \right) \times 100 \qquad (1)$$

where *Rm,t* is the stock return at month *m* of year *t*, *PRCCDeom,t*t represent the daily closing price at the last day of month *m* of year *t*, *PRCCDm0,t* represent the daily closing price at the first day of month *m* of year t, and the same notation applies to *AJEXDI* and *TRFD*.

Second, the weather data is collected from the National Oceanic and Atmospheric Administration website (https://www.ncdc.noaa.gov/cdo-web/), abbreviated as NOAA. After reviewing official websites of wine companies, we found producing origins of wine and wineries of each corporation and collected the relevant weather data for each corresponding place respectively. In this paper, we focus on the temperature, the precipitation, and wind speed.

The monthly stock return as a dependent variable corresponds weather data at given month as independent variables. Moreover, since planting season of the grape is an important consideration to wine quality, affecting market prices, it is reasonable to make some modifications on air temperature, precipitation, and wind speed, depending to whether current period is planting season or not. We assume the grape growing season is from May to September, and stock return data of year *m* corresponds weather data of this year. For months which is prior to planting months, people may look at weather situations from last year for reference, as a result, returns will also refer to average weather data of growing months of last year, that is, year *m-1*. For the rest months of this year *m*, investors thus far can access to weather data of planting season this year, so we used the average weather data of the grape growing months in current year. Accordingly, weather data is computed as:

$$TEMP_{m,t} = \begin{cases} TEMP_{[5,9],t-1}, \ \text{non} - \text{growing season}, m \in [1,4] \\ TEMP_{m,t}, \ \text{growing season}, m \in [5,9] \\ TEMP_{[5,9],t}, \ \text{non} - \text{growing season}, m \in [10,12] \end{cases} \qquad (2)$$

DOI: 10.54254/2754-1169/3/2022827

$$\mathrm{PREP}_{m,t} = \begin{cases} \mathrm{PREP}_{[5,9],t-1}, \text{ non} - \text{growing season}, m \in [1,4] \\ \mathrm{PREP}_{m,t}, \text{ growing season}, m \in [5,9] \\ \mathrm{PREP}_{[5,9],t}, \text{ non} - \text{growing season}, m \in [10,12] \end{cases} \tag{3}$$

$$\mathrm{WIND}_{m,t} = \begin{cases} \mathrm{WIND}_{[5,9],t-1}, \text{ non} - \text{growing season}, m \in [1,4] \\ \mathrm{WIND}_{m,t}, \text{ growing season}, m \in [5,9] \\ \mathrm{WIND}_{[5,9],t}, \text{ non} - \text{growing season}, m \in [10,12] \end{cases} \tag{4}$$

where *TEMPm,t*, *PREPm,t*, and *WINDm,t* respectively represent air temperature, precipitation amount, and wind speed in average at month *m* of year *t*.

Also, we introduced a categorical explanatory variable *SEASONm,t*, indicating whether the current month is in planting season or not. It sets value as one if current month is in planting season, that is, from May to September, otherwise, this variable takes value of zero.

Table 1: Variables Summary.

Variable Type	Variable Name	Comment
Independent	$\mathrm{TEMP}_{m,t}$	Average air temperature defined in month m of year t
	$\mathrm{PREP}_{m,t}$	Average amount of precipitation defined in month m of year t
	$\mathrm{WIND}_{m,t}$	Average wind speed defined in month m of year t
	$\mathrm{SEASON}_{m,t}$	Categorical variable indicating planting month (1: Yes; 0: No)
Dependent	$\mathrm{R}_{m,t}$	The return of stock of wine companies in month m of year t
	$\mathrm{S}_{m,t}$	Categorical variable for sign of return (1: Positive; 0: Negative)

3.2. Ordinary Least-Squares Regression Model

First, we adopt the least-squares regression model to investigate the weather effects as response values on the dependent variable: stock return. We examine our hypothesis by testing each explanatory weather variable:

$$\mathrm{R}_{m,t} = \beta_0 + \beta_i \mathrm{X}_{m,t} + \varepsilon_{m,t} \tag{5}$$

where $X_{m,t}$ is *TEMPm,t*, *PREPm,t*, and *WINDm,t* for individual model.

Three weather conditions, air temperature, precipitation, and wind speed, are all involved in this regression together. This model takes the following form:

$$\mathrm{R}_{m,t} = \beta_0 + \beta_1 \mathrm{TEMP}_{m,t} + \beta_2 \mathrm{PREP}_{m,t} + \beta_3 \mathrm{WIND}_{m,t} + \beta_4 \mathrm{SEASON}_{m,t} + \varepsilon_{m,t} \tag{6}$$

where β_i is the coefficients for the weather variables and $\varepsilon_{m,t}$ is error term. The result and interpretation of least-squares regression model will be displayed in the fourth section of this paper.

3.3. Logistic Regression Model

However, the linear regression is difficult to effectively test our hypothesis since the return is more likely a precise value. Hence, errors could be large, and it is possible that the result is not significant. As a result, the dependent variable becomes the sign of stock return in this model, meaning it is categorical now. It indicates whether the stock return is positive or negative by given month. When the stock return is positive, the dependent variable becomes 1, denoted as $S_{m,t}$ or $R_{m,t} > 0$; otherwise, the dependent variable becomes 0. With the same explanatory variables, logistic regression model takes the following form:

$$\mathbb{P}\left(\mathrm{R}_{\mathrm{m,t}} > 0\right) = \frac{1}{1+e^{-(\beta_0+\beta_i X_{m,t})}} \tag{7}$$

Similarly, we consider all weather conditions in the regression:

$$\mathbb{P}\left(\mathrm{R}_{\mathrm{m,t}} > 0\right) = \frac{1}{1+e^{-(\beta_0+\beta_1 \mathrm{TEMP}_{m,t}+\beta_2 \mathrm{PREP}_{m,t}+\beta_3 \mathrm{WIND}_{m,t}+\beta_4 \mathrm{SEASON}_{m,t})}} \tag{8}$$

3.4. Fixed Effect Regression Model

Since there are more than one wine corporation included in our panel data and we make the same estimation processes on each company, linear regression cannot show the difference between companies. Hence, repeated measurements, which are weather-related values, are made on the same unit of observation, which is company, in this scenario, which encourages to apply the fixed effect regression model. Under the company-fixed effect model, we control the effect of different wine companies specifically. Likewise, we also adopted year-fixed effect model and month-fixed effected model. The fixed effect model takes the form:

$$\mathrm{R}_{\mathrm{m,t}} = \beta_0 + \beta_1 \mathrm{TEMP}_{\mathrm{m,t}} + \beta_2 \mathrm{PREP}_{\mathrm{m,t}} + \beta_3 \mathrm{WIND}_{\mathrm{m,t}} + \beta_4 \mathrm{SEASON}_{\mathrm{m,t}} + \gamma_i \mathrm{D}_i + \varepsilon_{\mathrm{m,t}} \tag{9}$$

where D_i is control variable(s) described above, i.e., company, year, and month.

3.5. Multiple Regressions Including Interaction Terms Between Explanatory Variables

When we study the effect on returns of a change in one independent variable depends on another independent variable, we use an interaction term between these two factors. In our panel data, $SEASON_{m,t}$ is a binary variable and other weather conditions are continuous. By applying interaction terms, we can study, for instance, how returns of equity in the planting season of grape change from alternations in weather conditions differs to those in the non-planting season.

We introduce our baseline regressions, which are like previous OLS regressions, including one weather condition variable and $SEASON_{m,t}$. Under baseline models, we can measure the effect on stock returns of a change in one of weather condition with the same type of season, and study returns of being in a growing season holding the constant weather values, such as the same level of precipitation. This type of model follows the form:

$$R_{m,t} = \beta_0 + \beta_i X_{m,t} + \beta_S SEASON_{m,t} + \varepsilon_{m,t} \tag{10}$$

where $X_{m,t}$ is $TEMPm,t$, $PREPm,t$, and $WINDm,t$ for individual model.

Moreover, we can add an interaction term $(X_{m,t} \times SEASON_{m,t})$ in each model above, allowing us to observe the effect on returns of an increase in one unit of weather variables differs between planting season and non-planting seasons. In this case, the model is:

$$\mathrm{R}_{\mathrm{m,t}} = \beta_0 + \beta_i \mathrm{X}_{\mathrm{m,t}} + \beta_S \mathrm{SEASON}_{\mathrm{m,t}} + \beta_X (\mathrm{X}_{\mathrm{m,t}} \times \mathrm{SEASON}_{\mathrm{m,t}}) + \varepsilon_{\mathrm{m,t}} \tag{11}$$

Table 2: Econometric Models Summary.

Model	Regression Type	Variables	Comment
1	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \varepsilon_{m,t}$	\
2	OLS	$R_{m,t} = \beta_0 + \beta_2 PREP_{m,t} + \varepsilon_{m,t}$	\
3	OLS	$R_{m,t} = \beta_0 + \beta_3 WIND_{m,t} + \varepsilon_{m,t}$	\
4	OLS	$R_{m,t} = \beta_0 + \beta_4 SEASON_{m,t} + \varepsilon_{m,t}$	\
5	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \beta_2 PREP_{m,t} + \beta_3 WIND_{m,t} + \beta_4 SEASON_{m,t} + \varepsilon_{m,t}$	\
6	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \beta_2 PREP_{m,t} + \beta_3 WIND_{m,t} + \gamma_1 Company + \varepsilon_{m,t}$	Company-fix effect
7	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \beta_2 PREP_{m,t} + \beta_3 WIND_{m,t} + \gamma_2 Year + \varepsilon_{m,t}$	Year-fix effect
8	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \beta_2 PREP_{m,t} + \beta_3 WIND_{m,t} + \gamma_3 Month + \varepsilon_{m,t}$	Month-fix effect
9	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \beta_2 PREP_{m,t} + \beta_3 WIND_{m,t} + \gamma_1 Company + \gamma_2 Year + \gamma_3 Month + \varepsilon_{m,t}$	All three fix effect
10	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \beta_s SEASON_{m,t} + \varepsilon_{m,t}$	\
11	OLS	$R_{m,t} = \beta_0 + \beta_2 PREP_{m,t} + \beta_s SEASON_{m,t} + \varepsilon_{m,t}$	\
12	OLS	$R_{m,t} = \beta_0 + \beta_3 WIND_{m,t} + \beta_s SEASON_{m,t} + \varepsilon_{m,t}$	\
13	OLS	$R_{m,t} = \beta_0 + \beta_1 TEMP_{m,t} + \beta_s SEASON_{m,t} + \beta_X (TEMP_{m,t} \times \beta_s SEASON_{m,t}) + \varepsilon_{m,t}$	interaction term: temp × season
14	OLS	$R_{m,t} = \beta_0 + \beta_2 PREP_{m,t} + \beta_s SEASON_{m,t} + \beta_X (PREP_{m,t} \times \beta_s SEASON_{m,t}) + \varepsilon_{m,t}$	interaction term: Prep × season
15	OLS	$R_{m,t} = \beta_0 + \beta_3 WIND_{m,t} + \beta_s SEASON_{m,t} + \beta_X (WIND_{m,t} \times \beta_s SEASON_{m,t}) + \varepsilon_{m,t}$	interaction term: wind × season
16	Logit	$\mathbb{P}(R_{m,t} > 0) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 TEMP_{m,t})}}$	\
17	Logit	$\mathbb{P}(R_{m,t} > 0) = \frac{1}{1 + e^{-(\beta_0 + \beta_2 PREP_{m,t})}}$	\
18	Logit	$\mathbb{P}(R_{m,t} > 0) = \frac{1}{1 + e^{-(\beta_0 + \beta_3 WIND_{m,t})}}$	\
19	Logit	$\mathbb{P}(R_{m,t} > 0) = \frac{1}{1 + e^{-(\beta_0 + \beta_4 SEASON_{m,t})}}$	\
20	Logit	$\mathbb{P}(R_{m,t} > 0) = 1/(1 + \exp(-\beta_0 + \beta_1 TEMP_{m,t} + \beta_2 PREP_{m,t} + \beta_3 WIND_{m,t} + \beta_4 SEASON_{m,t}))$	\

4. Results

4.1. Descriptive Statistics

Table 3 displays a summary of descriptive statistics that comes from the sample data. For binary variables, counts of 1 and 0 are recorded. Table 4 displays correlation coefficients between explanatory weather factors. Not surprisingly, these correlations are not extremely high, which are probably all less than 0.7.

DOI: 10.54254/2754-1169/3/2022827

Table 3: Statistics Summary.

Name	Median	Mean	Std. Dev	Min	Max	#1	#0
Independent Variables:							
$TEMP_{m,t}$ (Celsius)	69.94	71.13	6.357	53.50	80.52	/	/
$PREP_{m,t}$ (Millimeters)	2.272	2.653	2.118	0.002	8.605	/	/
$WIND_{m,t}$ (Meters per second)	6.675	6.633	0.674	5.000	8.670	/	/
$PLANT_{m,t}$	/	/	/	/	/	180	252
Response Variables:							
$R_{m,t}$ (Unit: %)	0.682	1.176	6.005	-18.864	44.243	/	/
$S_{m,t}$	/	/	/	/	/	248	184

Table 4: Correlation Matrix.

	$TEMP_{m,t}$	$PREP_{m,t}$	$WIND_{m,t}$
$TEMP_{m,t}$	1		
$PREP_{m,t}$	0.7162	1	
$WIND_{m,t}$	0.6391	0.5946	1

4.2. Ordinary Least-Squares Regression Model

By least-squares regression model, the result shows the level of precipitation is significant, but other factors, the average temperature and wind speed, are insignificant.

Table 5a: OLS Models Summary.

Model	Intercept	TEMP	PREP	WIND	SEASON (=1)	Firm-fix effect	Year-fix effect	Month-fix effect
1	0.4566 (3.253)	0.01011 (0.046)	\	\	\	No	No	No
2	1.68*** (0.463)	\	-0.1897 (0.136)	\	\	No	No	No
3	0.847 (2.863)	\	\	0.0496 (0.430)	\	No	No	No
4	1.423*** (0.378)	\	\	\	-0.593 (0.586)	No	No	No
5	-6.1488 (4.6943)	0.0834 (0.073)	-0.447* (0.2029)	0.4191 (0.5894)	0.4895 (0.6111)	No	No	No
6	\	0.1206 (0.1115)	-0.2644 (0.3751)	0.2386 (0.7318)	\	Yes	No	No
7	\	0.1249. (0.0708)	-0.629** (0.2071)	0.7895 (0.6117)	\	No	Yes	No
8	\	0.0248 (0.1090)	-0.376. (0.2215)	0.7101 (0.778)	\	No	No	Yes
9	\	0.1357 (0.2034)	-0.4397 (0.3985)	1.664 (1.0204)	\	Yes	Yes	Yes

The estimated coefficient of precipitation level is significantly different from zero in model 5, and the value of this coefficient (-0.447) is negative statistically. Employing least-squares regression model, the results interpret that the monthly level of precipitation in wine producing area is negatively correlated to the stock return. Once the amount of precipitation increases, the monthly stock return of

DOI: 10.54254/2754-1169/3/2022827

related wine companies will be lower. In model 2, the intercept term has meaningful interpretation if the level of precipitation is zero or nearly zero. Then, the return of equity is expected to have an average value of 1.168 percentage for nearly null value of precipitation.

By controlling the year fixed effect, we can estimate the relationship between returns and weather conditions; obviously, the precipitation variable become more significant under year-fix effect model. To the contrary, the company-specific fix effect model and month-fix effect model do not optimize results.

Table 5b: OLS Regression Results (Interaction Terms).

Model	Intercept	TEMP	PREP	WIND	SEASON (=1)	X*SEASON (X: weather)	Interaction terms
10	1.119 (3.321)	0.00423 (0.046)	\	\	-0.586 (0.592)	\	No
11	1.917*** (0.521)	\	-0.188 (0.137)	\	-0.5827 (0.5854)	\	No
12	0.7914 (2.863)	\	\	0.0961 (0.432)	-0.607 (0.58989)	\	No
13	0.5255 (4.38306)	0.0125 (0.0608)	\	\	0.7829 (6.61367)	-0.01932 (0.09295)	Yes
14	1.595** (0.6112)	\	-0.0655 (0.1827)	\	0.15427 (0.93646)	-0.277 (0.2748)	Yes
15	-0.9512 (4.024)	\	\	0.3612 (0.6094)	2.9348 (5.7724)	-0.5329 (0.8641)	Yes

From Table 5b, we can compare effects on returns of an increase in one specific weather variables are different from planting seasons and non-planting seasons. The coefficient on the interaction term in model 14 indicates the difference of two (season) effects is about 0.277 percent of returns. After computation, we get marginal results. When current month is not in planting season (SEASON = 0), estimation of marginal change in returns is -0.0655. For planting seasons (SEASON = 1), the marginal effect estimates of stock returns is -0.3425. It implies, by one unit increase in level of precipitation, the decreased amount of return is nearly 0.3425 percent when it is in planting months, whereas it will be reduced by 0.0655 when it is in non-planting months.

4.3. Logistic Regression Model

Hirshleifer and Shumway (2003) examine their hypothesis that the sunny weather is strongly associated with relatively high stock market returns by using both least-squares and logit regression models. We adopt the logistic regression to keep consistence with models of Hirshleifer and Shumway (2003). Under logistic model, the dependent variable is binary, which is equal to one if the stock return in current month is positive, otherwise, it has a negative sign.

Table 6: Logit Models Summary (in raw coefficients).

Model	Intercept	TEMP	PREP	WIND	SEASON (=1)	Firm-fix effect	Year-fix effect	Month-fix effect
16	-1.36 (1.0961)	0.02334 (0.01538)	\	\	\	No	No	No
17	0.251 (0.1557)	\	0.0178 (0.046)	\	\	No	No	No
18	-0.341 (0.9634)	\	\	0.09651 (0.1446)	\	No	No	No
19	0.5363*** (0.1305)	\	\	\	-0.5585** (0.198)	No	No	No
20	-1.5943 (1.592)	0.0238 (0.02474)	-0.0468 (0.0689)	0.0829 (0.19966)	-0.53054* (0.207)	No	No	No

DOI: 10.54254/2754-1169/3/2022827

Results are summarized in Table 6, demonstrating that three weather factors are not significantly correlated with sign of stock return. Instead, the categorical growing season indicator variable shows significance statistically, suggesting the planting months influence the sign of stock returns. In model 19, the intercept is when the current month is not in planting season, meanwhile, the explanatory variable is planting season months. Overall, the estimated coefficient of categorical planting season variable is negative (-0.53054), implying whether current month is in planting season is oppositely associated with higher probability of being positive stock return. With non-planting season as reference, the odd ratio is computed to be 0.572, meaning the odds of having positive returns in planting season months is 42.8% less likely as compared to non-planting season.

5. Conclusion

Weather conditions are important to prices of bottle wine. Based on previous psychological literatures, weather could affect the stock exchange. Therefore, this paper aims to test the hypothesis that weather-related factors will also influence the stock return of companies whose primary business is fine wine. In the light of results from previous section, our data suggests that the level of precipitation is negatively affected monthly stock returns, whereas the monthly average air temperature and wind speed are not correlated with stock returns in our research. Whenever the amount of precipitation increases one unit, the corresponding stock return of wine companies will decrease. This finding is consistence with the result of Hirshleifer and Shumway [9], which is there is a positive correlation between sunshine and stock returns, since high level of precipitation means less sunny weather. In this paper, the stock market is not sensitive to temperature factors, even though there are a great number of evidence that proved the temperature is strongly associated with the wine pricing, for instance, Ashenfelter [7] has shed light on hot and dry summers can result in vintages with higher prices for mature fine wines.

When we control fixed effect of years, the precipitation variable become more significant in estimations of returns. However, other control variables have no contributions to improve our models. Since we include dummy variables in regressions, we use interaction terms to compare the gap of returns estimated by weather factors in planting season and non-planting season. For example, as the level of precipitation augments by one unit, the marginal decrease of stock return is much higher in planting season.

We also find the sign of monthly stock returns is more likely to be determined by the binary explanatory variable of whether current month is growing month rather than specific weather conditions. Our result indicates that the probability of positive stock return is lower for planting season than for non-planting season months, which is not intuitive. One potential reason may relate to unknown and relatively more risky growing seasons months of grape. On the other hand, investors and economists can obtain more reference information to make decisions during non-growing seasons. Based on our results, investors are more likely to achieve interest arbitrage in non-growing season months of the grapes.

One limitation of this study is the size of our sample is not sufficient, we only collected four NYSE-listed wine companies in a decade. As for weather data, there exists missing values for some detection stations of wine origins, which reduced the precision of monthly weather variables. Moreover, since listed corporations are huge in scale, they operate a mass of products. Hence, some other wines and production places might not be covered in this paper.

References

[1] *Storchmann, K. (2012). Wine Economics. Journal of Wine Economics, 7(1), 1-33.*

[2] *Jones, G. V., & Storchmann, K. H. (2001). Wine market prices and investment under uncertainty: an econometric model for Bordeaux Crus Classés. Agricultural Economics, 26(2), 115-133.*

[3] Arias - Bolzmann, L., Sak, O., Musalem, A., Lodish, L., Báez K., R. and José De Sousa, L. (2003), Wine Pricing: The Influence of Country of Origin, Variety, and Wine Magazine Ratings, International Journal of Wine Marketing, Vol. 15 No. 2, pp. 47-57.
[4] Jiao, L. (2017), Macroeconomic determinants of wine prices, International Journal of Wine Business Research, Vol. 29 No. 3, pp. 234-250.
[5] Oleksy, P., Czupryna, M., & Jakubczyk, M. (2021). On Fine Wine Pricing across Different Trading Venues. Journal of Wine Economics, 16(2), 189-209.
[6] Ramirez, C. (2008). Wine Quality, Wine Prices, and the Weather: Is Napa "Different"? Journal of Wine Economics, 3(2), 114-131.
[7] Ashenfelter, O. (2008). Predicting the Quality and Prices of Bordeaux Wine. The Economic Journal, 118(529), 174–184.
[8] Oczkowski, E. (2016). The Effect of Weather on Wine Quality and Prices: An Australian Spatial Analysis. Journal of Wine Economics, 11(1), 48-65.
[9] Hirshleifer, D., & Shumway, T. (2003). Good day sunshine: Stock returns and the weather. The journal of Finance, 58(3), 1009-1032.
[10] Floros, C. (2011), On the relationship between weather and stock market returns, Studies in Economics and Finance, Vol. 28 No. 1, pp. 5-13.
[11] Loughran, T., & Schultz, P. (2004). Weather, Stock Returns, and the Impact of Localized Trading Behavior. Journal of Financial and Quantitative Analysis, 39(2), 343-364.
[12] Sariannidis, N., Giannarakis, G. and Partalidou, X. (2016), The effect of weather on the European stock market: The case of Dow Jones Sustainability Europe Index, International Journal of Social Economics, Vol. 43 No. 9, pp. 943-958.
[13] Goetzmann, W. N., Kim, D., Kumar, A., & Wang, Q. (2014). Weather-Induced Mood, Institutional Investors, and Stock Returns. Review of Financial Studies, 28(1), 73–111.