

TESTING HEDONIC THEORIES USING ONLINE DATA

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Abstract

The theme of this thesis is the use of online data to test hedonic theories. “Hedonic theories” are theories which embody the idea that consumer behaviour is motivated by the pursuit of satisfaction. Online market data is very useful in the testing of such theories, because it often includes large amounts of information in the form of customer reviews, which represent a natural measure of customer satisfaction. In some hedonic theories, customer satisfaction data is used to explain outcomes such as product price, producer’s sales volume, or customer purchase intentions. In other hedonic theories, customer satisfaction takes the role of the the dependent variable, and the focus is on the features of the product (including price) which influence satisfaction.

The thesis comprises three main chapters.

In the first main chapter, a meta-analysis is conducted to investigate and explain between-study differences in the estimated effects of electronic word of mouth (eWOM) on consumer behavior outcomes, such as purchase intentions and actual sales, in peer-to-peer online markets. Drawing from 155 studies and analyzing 836 reported effects, the research explores the factors that influence the significance of eWOM-related reputation effects. Using meta-regression analysis, we find that larger sample sizes are consistently associated with more statistically significant results, in line with expectations from statistical theory. The study also reveals important geographic variations, with studies from Asian countries showing higher significance levels compared to those from other regions. Additionally, the analysis highlights a noticeable shift in findings for studies published after 2020, where lower significance levels are observed, potentially reflecting a fall-off in consumer trust in online reviews following the COVID-19 pandemic. Furthermore, our results show that experimental studies are more likely to yield significant outcomes than observational ones, possibly due to their controlled environments that allow for clearer causal inferences. These findings contribute to the broader understanding of how eWOM impacts consumer behavior across different contexts and offer valuable insights for future research on

online reputation systems.

In the second and third main chapters, the focus narrows to a particular online market: wine. The second main chapter presents a Hedonic Pricing Model for wine, focusing on the impact of weather conditions prevailing during the year in which the wine was produced on the current prices of red and white wines across different regions of the world. This study expands upon the work of Ashenfelter et al. (1995), who used weather variables to explain the prices of Bordeaux wines. Our extension is that we incorporate a more diverse global dataset. The research aims to identify how variations in temperature and rainfall during the grape growing, maturation, and harvest seasons influence wine prices. By including regional dummies, we are also allowing for regional differences in “terroir” (that is, the environment in which the wine is produced, including factors such as the soil, topography, and method of production). We find that an array of weather variables observed around the time of production of the wine, have a significant effect on the current prices of the wines. These sorts of results are clearly very useful for wine producers, investors, and policymakers, since they provide a means of predicting the future quality of a wine at (or even before) the time at which the wine is produced. More importantly for our own purposes, these results provide a valid set of instrumental variables which allow for the possible endogeneity of the price variable in the analysis conducted in the final main chapter of the thesis.

In the third and final main chapter, Online customer review data is used, together with price data, to test the hypothesis that wine is a “Veblen Good” (Veblen, 1899). We define a Veblen good as a good which becomes more desirable to consumers as the price increases, even after controlling for true quality. The Veblen phenomenon is very interesting to economists because it can be perceived as a violation of the almost universal “Law of Demand”. The test is performed in the context of a weighted regression model with average customer rating as the dependent variable, and the log of price as an independent variable. The key to the empirical strategy is that the “true quality” of the wine is controlled for, by including a measure of “expert rating” as an independent variable in the regression. As mentioned above, we also allow for possible endogeneity of price using weather variables in the year of production as instruments. We find strong evidence of the Veblen effect for red wine, but no such effect for white wine.

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Chapter 1

Introduction

In the current era of rapid internet development, many industries have transitioned from traditional bricks-and-mortar markets to online shopping platforms. For instance, consumers now primarily purchase products such as clothing, daily necessities, and household appliances via the internet. This shift has not only streamlined the shopping process, reducing time and costs for consumers, but has also driven the rise of major e-commerce platforms, enabling individuals to not only shop but also sell products online.

However, the convenience of online shopping has introduced a critical challenge: consumers are unable to physically inspect or verify the quality of products before making a purchase. It is only upon receiving the product that they can assess its actual condition. In response to this issue, online review systems have emerged. These systems aggregate consumer feedback and evaluations, allowing potential buyers to gain a more comprehensive understanding of both the product and the seller before making a purchase. By reviewing product descriptions, seller ratings, and other customer feedback, consumers are able to make more informed decisions regarding the quality of products and the reliability of sellers, thereby improving the online shopping experience.

With the increasing prevalence of online review systems, a growing number of consumers now prefer to shop on digital platforms. According to surveys (Khare, 2016), the majority of consumers have shifted towards online shopping, gradually replacing traditional offline purchasing methods. This trend offers a wealth of data for studying consumer behavior in online contexts, providing insights that were previously unattainable due to insufficient data availability. The analysis of these data not only enhances our understanding of consumer preferences and behaviors but also supports research that has long lacked adequate data for meaningful conclusions.

Thus, examining this data is of significant importance for understanding contemporary consumer behavior and offers new avenues for both commercial and academic research.

The theme of this thesis is the testing of hedonic theories using online data. “Hedonic theories” are theories which embody the idea that consumer behaviour is motivated by the pursuit of satisfaction. Online market data is very useful in the testing of such theories, because it often includes large amounts of information in the form of customer reviews, which provide a natural measure of consumer satisfaction. In some hedonic theories, customer satisfaction data is used to explain outcomes such as product price, producer’s sales volume, or customer purchase intentions. In other hedonic theories, customer satisfaction takes the role of the the dependent variable, and the focus is on the features of the product (including price) which influence satisfaction.

The thesis contains three progressively structured main chapters. First, Chapter 2 reports on a meta analysis covering the literature on electronic word of mouth (eWOM). There is already a reasonably large literature on the effectiveness of eWOM, in determining such outcomes as consumer purchase intentions, price mark-ups, and sales. Needless to say, there are differences in results between studies. Chapter 2 sets out to explain these differences by applying techniques of meta analysis to a set of results from collected studies. Each study contains one or more statistical tests of the significance of eWOM on particular outcomes. In order to make the tests comparable, we use the p-value (or “observed significance”) of each test as the dependent variable in the meta-analysis. In fact, in order to deal with the strong skewness in the distribution of p-values, we use the transformation $-\ln(\text{p-value})$ as the dependent variable, and this variable can be interpreted as a direct measure, taking values between 0 and ∞ , of the statistical significance of eWOM detected by the test. The use of p-values in meta analysis has been made before (Loughin, 2004). The econometric challenge that is faced here is that in the studies making up the data set, not all of the p-values are exactly observed. For example, in some studies, tests are simply accompanied by a number of “stars” indicating a level of significance, e.g. 5%, 1%, etc. When only this sort of information is available, the p-value is not known exactly, but is known to lie in an interval. For this reason, the interval regression estimator is required in place of the OLS estimator.

In Chapters 3 and 4, the focus narrows to a particular online market: wine.

Chapter 3 presents a Hedonic Pricing Model for wine, focusing on the impact of weather conditions prevailing during the year in which the wine was produced. Similar goals have been pursued previously by Ashenfelter et al. (1995), although that study restricted itself to Bordeaux wines, while we consider wines from all over the Northern hemisphere. The principal aim to the research is to identify how variations in temperature and rainfall during the grape growing, maturation, and harvest seasons influence current wine prices. Chapter 3 has a strong link to Chapter 4, because the weather variables identified as being important in the hedonic pricing model of Chapter 3, are used as valid instruments to account for the possible endogeneity of price in the model of Chapter 4.

In Chapter 4, online customer review data is used, together with price data, to test the hypothesis that wine is a “Veblen Good” (Veblen, 1899). We define a Veblen good as a good which becomes more desirable to consumers as the price increases, even after controlling for true quality. The Veblen phenomenon is very interesting to economists because it can be perceived as a violation of the almost universal “Law of Demand”. The test is performed in the context of a weighted regression model with average customer rating as the dependent variable, and the log of price as an independent variable. The key to the empirical strategy is that the “true quality” of the wine is controlled for, by including a measure of “expert rating” as an independent variable in the regression. As mentioned above, we also allow for possible endogeneity of price using weather variables in the year of production as instruments.

The three main chapters in this dissertation revolve around a common theme: testing hedonic theories using online data to explore the complex relationship between consumer decision-making and pricing. Although each chapter has a different research focus, they are closely connected through the use of online data on customer reviews and product prices.

Chapter 2

A Meta-Analysis of eWOM Effects

2.1 Introduction

Word of mouth (WOM) refers to the communication of information about products, services, brands, or companies between consumers (Greif, 1989; Hillmann, 2013; Diekmann et al., 2019; Robledo et al., 2023). When this information is shared online through reviews, tweets, blog posts, likes, pins, images, or video testimonials, it is referred to as electronic word of mouth (eWOM), one of the most significant forces shaping modern consumer behavior (Dellarocas, 2003; Gregg and Scott, 2006; Li et al., 2019). With the rise of the internet and the increasing prevalence of online shopping platforms, eWOM has become widespread, enabling consumers to share their opinions and experiences with a vast audience. Businesses are increasingly recognizing the importance of gathering and managing eWOM to enhance sales (Blackshaw and Nazzaro, 2006). Research shows that eWOM plays a crucial role in influencing online shopping decisions, as users often rely on peer reviews and recommendations when evaluating products and services (Khare, 2016).

Moreover, eWOM also contributes to governance and corporate social responsibility by enhancing market transparency (Ngo et al., 2024; Khan et al., 2024), by providing consumers with accessible and reliable information about product quality, corporate ethical practices, and sustainability commitments (Saqib et al., 2025; Mim et al., 2022). Through online reviews, ratings, and user-generated content, eWOM enables consumers to make informed decisions, hold businesses accountable for their ESG performance, and promote responsible corporate behavior (Ahmad et al., 2022). Additionally, eWOM fosters trust in digital marketplaces by reducing information asymmetry and encouraging businesses to adopt transparent and socially responsible practices to maintain a positive reputation (Sang, 2022; Liu et al., 2022).

While the market and social significance of eWOM is widely acknowledged, the question of how to effectively manage eWOM and what factors influence its impact remains unresolved (Livingston, 2005; Snijders and Weesie, 2009; Jabr, 2022). This study addresses these gaps in the literature through a meta-analysis, focusing on three key aspects of eWOM research where consensus has yet to be reached.

First, this study examines how country-specific and cultural factors influence the effect of eWOM. By comparing the degree to which consumers across different countries respond to eWOM, we can identify which regions show stronger or weaker sensitivity to online reputation signals. These variations reflect underlying differences

in how consumers perceive and react to peer-generated content across cultural contexts. Understanding such differences is valuable for designing localized eWOM strategies that align with the attitudes and behaviors of consumers in each market. Although previous studies have explored cross-cultural differences in eWOM (Yao et al., 2019; Chu and Kim, 2011; Kusawat and Teerakapibal, 2022), they are often constrained by limited sample scope and lack global generalizability. This study incorporates data from a broader set of regions, including Asia, Europe, and the United States, to offer a more systematic comparison of how eWOM effectiveness varies across countries and cultures.

Second, this study compares the effect of eWOM on consumers' purchase intentions and their actual purchasing behavior. While previous meta-analyses have generally focused on only one of these two outcomes, either purchase intention or actual sales performance (Babić Rosario et al., 2016; Ismagilova et al., 2020). Little is known about whether findings across these studies are comparable or reflect fundamentally different aspects of consumer response. This distinction matters because intention and behavior often diverge: consumers may express willingness to buy in a controlled setting, but not follow through in real-world contexts. This phenomenon, known as the intention–behavior gap (Ajzen, 1980), poses a critical challenge to interpreting eWOM's true market impact. Moreover, the two outcomes are typically studied using different methodologies, experiments for intentions and observational data for actual purchases, raising questions about how design factors may influence observed effects. By integrating both types of studies into a single meta-analytic framework, this research provides a unique opportunity to examine whether eWOM effects consistently translate from consumer attitudes into consumer actions. The findings thus contribute to both academic theory and managerial practice by clarifying the extent to which eWOM is capable of driving real economic outcomes, not just shaping perceptions.

Thirdly, this study investigates how consumers' attitudes toward eWOM have evolved over time. With the growing volume of online transactions and the widespread adoption of review platforms, consumers have become increasingly familiar with the mechanisms of eWOM. However, this increased familiarity raises an important question: do consumers still trust eWOM as much as they did in its early years? As eWOM has become a crucial element of digital commerce, businesses have recognized its influence on their sales and reputations, leading to a rise in strategic eWOM management practices—including fake reviews, artificially boosted ratings, and malicious negative reviews aimed at competitors.

The COVID-19 pandemic further accelerated these dynamics, as online shopping surged to unprecedented levels, making eWOM more integral to consumer decision-making than ever before. While the pandemic strengthened consumers' reliance on digital marketplaces, it also intensified concerns regarding the authenticity of eWOM. The increased prevalence of misleading information, fake reviews, and review manipulation tactics has led to a notable decline in consumer trust in eWOM, particularly in post-2020 studies. To examine these shifting perceptions, this study incorporates data up to 2022, providing insights into how trust in eWOM has changed in response to evolving market practices and digital shopping behaviors.

By integrating these factors, this study provides a comprehensive overview of the key factors influencing the statistical significance of eWOM effects. The findings offer valuable guidance for future research and contribute to a deeper understanding of the impact of online reputation in digital marketplaces.

This study adopts a meta-regression approach using p-values as the dependent variable. This choice is motivated by the substantial heterogeneity in research foci among the studies included in the analysis. Specifically, prior eWOM studies examine a wide range of outcomes—from price premium, repurchase intention, and brand loyalty, to consumers' likelihood of recommending a product to others. Because these outcomes are conceptually distinct and measured using different scales, effect sizes are not directly comparable across studies. Consequently, p-values offer a standardized metric that allows for a coherent aggregation and comparison of statistical significance, regardless of the specific outcome variable employed. This approach also aligns with existing methodological frameworks in meta-analysis when effect size harmonization is not feasible due to outcome diversity.

2.2 Literature Review

Electronic word of mouth (eWOM) refers to the online communication of product, service, or brand information between consumers (McFadden and Train, 1996; Smallwood and Conlisk, 1979; Banerjee, 1992, 1993; Kirman, 1993; Ellison and Fudenberg, 1995). With the rise of e-commerce platforms, eWOM has become a vital force in shaping consumer behavior, corporate reputation, and market outcomes (Chevalier and Mayzlin, 2006; Duan et al., 2008; Kozinets et al., 2010). eWOM

operates in complex online environments that differ from traditional WOM by their larger reach, persistence, anonymity, and potential for manipulation (Dellarocas, 2003; Hennig-Thurau et al., 2010; Resnick et al., 2000; Mudambi and Schuff, 2010). These characteristics enable eWOM to simultaneously raise product awareness and shape consumer evaluations (Duan et al., 2008; Floyd et al., 2014; King et al., 2014; Babić Rosario et al., 2016), though they also introduce challenges in credibility, as firms may engage in practices that artificially enhance ratings or generate fake reviews (Ballantine and Au Yeung, 2015; Verma and Dewani, 2021).

Prior studies have explored how cultural and geographic factors influence eWOM's impact. Consumers from collectivist cultures may value consensus and harmony, showing different review behaviors compared to those from individualist cultures who emphasize personal expression (Aaker and Maheswaran, 1997; De Mooij and Hofstede, 2011; Fong and Burton, 2006; Kusawat and Teerakapibal, 2021). Such cultural orientations shape how reviews are generated, interpreted, and acted upon. Moreover, temporal changes, particularly the growth of online shopping and the COVID-19 pandemic, have heightened concerns about eWOM authenticity and consumer trust, as digital marketplaces face increased manipulation risks (Cheung et al., 2009; Ismagilova et al., 2017; King et al., 2014; Hwang and Jeong, 2016; Jensen et al., 2013; Park and Lee, 2008). This evolving landscape makes it critical to assess whether eWOM's significance has shifted over time.

However, synthesizing these diverse studies poses methodological challenges, as traditional effect-size meta-analyses struggle to accommodate the heterogeneity of outcomes, designs, and measurement practices found in eWOM research. To address this gap, our study adopts a p-value based approach, as also applied in previous meta-regression analyses by Loughin (2004) and Aliyu (2010), which offers a common ground for comparing statistical significance across contexts. Given this substantial heterogeneity, focusing on p-values provides a standardized metric that enables the meta-analysis to identify broader patterns of reported significance that might otherwise be obscured. Furthermore, p-values reflect the combined influence of sample size, effect magnitude, and study precision, offering valuable insights into how consistently eWOM demonstrates a statistically detectable impact across the literature. This approach complements traditional effect-size analyses and is particularly well-suited for synthesizing findings across studies that differ markedly in design and reporting practices.

In terms of research methodologies, experimental studies often report stronger

eWOM effects due to greater control over variables, while observational studies reflect real-world complexities but may capture weaker or confounded relationships (Aliyu, 2010). Understanding how methodological choices influence reported eWOM significance is essential for interpreting the literature and guiding future research designs.

Previous meta-analyses have largely examined either purchase intention or actual purchase behavior in isolation. For example, Albayrak and Ceylan (2021) focused on how eWOM influences purchase intention, considering factors like argument quality and source credibility, while Jiao et al. (2021) analyzed how seller reputation affects actual sales and price outcomes in peer-to-peer markets. These studies provide valuable insights but treat intention and action as separate processes. In contrast, our meta-analysis integrates both outcomes within a single framework, allowing us to investigate how eWOM influences the full consumer decision-making path. Furthermore, by using p-values as the dependent variable, following the meta-regression approaches of Loughin (2004) and Aliyu (2010), we provide a common metric for comparing results across diverse contexts and designs. This approach addresses the heterogeneity that limits traditional effect-size meta-analyses and offers new insights into patterns of reported significance in eWOM research.

2.2.1 Research Questions and Hypotheses

Based on the gaps identified in the literature and the objectives outlined above, this study seeks to answer the following research questions:

- How do country-specific and cultural factors influence the statistical significance of eWOM effects?
- Does eWOM influence purchase intentions and actual purchasing behavior to the same extent?
- How have consumer attitudes toward eWOM and its significance changed over time?

The study tests hypotheses related to these questions by examining how geographic region, publication timing, and research method affect the likelihood and strength of statistically significant eWOM effects. In doing so, the meta-analysis contributes to a deeper understanding of eWOM's impact on consumer trust, purchase intentions, and actual market behavior across different digital commerce settings.

2.3 A Small Monte-Carlo Study

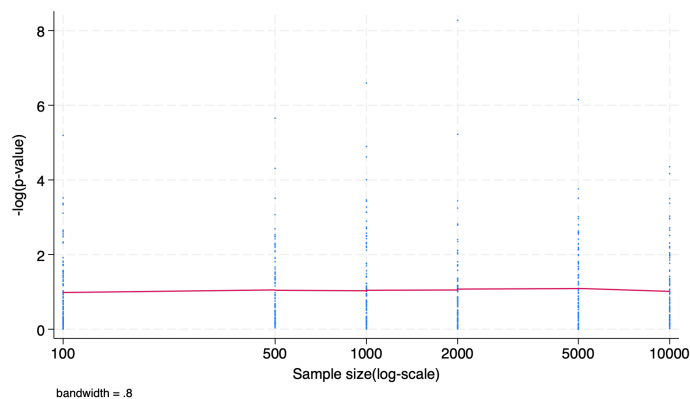
As mentioned in Section 2.2 above, we are following Loughin (2004) and Aliyu (2010) by basing our meta analysis on p-values of statistical tests of the significance of eWOM. In this section, we perform a simple Monte Carlo experiment which shows the likely patterns to be seen when analysing p-values in this way.

The Data Generating Process (DGP) for the Monte Carlo experiment is:

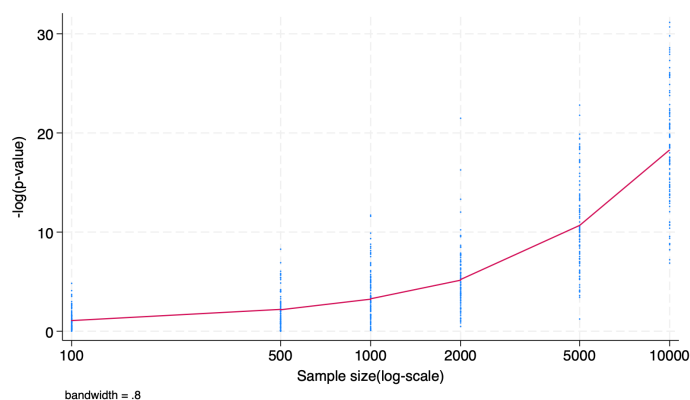
$$\begin{aligned}y_i &= 10.0 + \beta x_i + u_i & i = 1, \dots, n \\x_i &\sim U(0, 1) \\u_i &\sim N(0, 1)\end{aligned}\tag{2.1}$$

In 2.1, the variable x corresponds to the eWOM variable, while the variable y corresponds to the outcome variable (e.g. sales). For each sample of size n simulated using 2.1, the null hypothesis $H_0 : \beta = 0$ is tested using a t-test, and the resulting p-value is stored. We are interested to know how the distribution of p-values changes when β and n are varied.

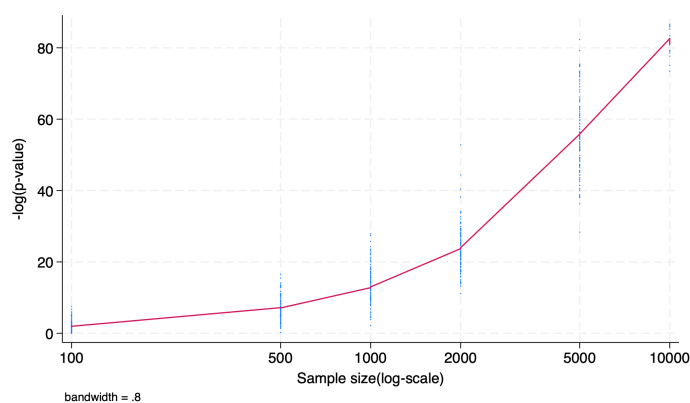
The dependent variable in our meta analysis will be $-\log(p\text{-value})$, since this transformation avoids the skewness seen in the distribution of p-values, and also provides a direct measure of the significance of the effect. Figure 2.1 shows simulated (transformed) p-values against the sample size n , for different values of the true regression slope β . First of all, we see that when the true regression slope is zero (i.e. when eWOM truly has no effect), the measure of significance do not increase with the sample size. This is expected: if there is truly no effect, an increase in the sample size will not increase the likelihood of finding a significant effect. However, when the true regression slope (β) is positive, an increase in the sample size does result in an increase in our measure of significance, and the larger the value of β , the steeper the increase.



(a) Monte Carlo experiment 1: True regression slope equals 0.



(b) Monte Carlo experiment 2: True regression slope equals 0.2.



(c) Monte Carlo experiment 3: True regression slope equals 0.5.

Figure 2.1: Monte Carlo Experiments with different true regression slopes. 100 replications at each sample size. Each graph shows $-\log(p\text{-value})$ against sample size (log-scale). Lowess smoothers superimposed.

This simple Monte Carlo experiment has two important implications. First, a

positive effect of sample size in the meta-regression may be taken as evidence that, based on the entire literature, eWOM has a positive effect on the outcomes being considered. Second, the positive effect of the sample size is expected on the basis of statistical theory. It is therefore obvious that the sample size (or its logarithm) should be included as an independent variable in the meta analysis. The focus of the meta analysis is then whether the other independent variables, for example geographical location and year of publication, have an effect on the outcome over and above the effect of the sample size.

2.4 Data

2.4.1 Data Sources

The primary dataset used in this study was obtained from the authors of the paper Reputation Effects in Peer-to-Peer Online Markets: A Meta-Analysis (Jiao et al., 2021). This dataset contains information on reputation effects, selling performance, and customer behavior across multiple peer-to-peer online markets. Key variables include seller reputation indicators (such as positive and negative ratings, overall rating scores) and various measures of selling performance (like probability of sale, selling price, and selling volume).

The dataset from Jiao et al. (2021) originally includes 107 studies published between 1999 and 2017. A complete list of these studies is provided in Jiao et al. (2021). In order to capture more recent papers, I extended the dataset to include additional studies published after 2018. The expanded dataset now includes an additional 47 studies, with papers up to 2022. The full list of additional papers included in the analysis can be found in Figure 2.7 in the Appendix. The newly incorporated studies maintain the criteria used in the original research but provide insights that reflect the recent evolution of peer-to-peer market reputation effects.

The integration of both datasets not only preserves the methodological consistency established in the original paper but also allows for a more comprehensive analysis that includes recent trends in online markets.

2.4.1.1 Examples

The purpose of this subsection is to attempt to convey an idea of the process used to collect data for the meta analysis. We use specific examples of publications from which data was extracted.

Figures 2.2 and 2.3 show screenshots from Eddhir (2009) and Jin and Kato (2006), respectively. In Figure 2.2, the exact p-values are reported, while in Figure 2.3, the only available information is in the form of star symbols (*, **, or ***), from which it is possible to infer intervals for the p-value. These examples are useful for illustrating why the meta data set contains a combination of exact p-values and intervals for p-values.

In Figure 2.2, the exact p-values are reported, for a model in which the dependent variable is the number of successful bids achieved by the seller on eBay and the independent variable is the percentage of positive ratings left by members in the last 12 months. The circled values are the exact p-values indicating the strengths of the effect of positive feedback on the seller's number of winning bids.

Table A.1: Linear regression results

Full Sample, 129 obs.					
Model Number	1	2	3	4	5
Positive Feedback (Pfb)	.001866 (0.371)	—	.0005927 (0.749)	—	-.0027167 (0.313)
Negative Feedback (Nfb)	—	.4089057 (0.293)	—	.4723027 (0.167)	.8406628 (0.094)
Number of bid (Nbid)	—	—	1.278308 (0.000)	1.308225 (0.000)	1.370605 (0.000)
Time (t)	—	—	.2072516 (0.879)	.0597209 (0.965)	-.0200941 (0.988)
Shipping cost (Scost)	—	—	-1.208414 (0.031)	-1.218924 (0.028)	-1.210247 (0.030)
Starting Bid (Sbid)	—	—	.039904 (0.666)	.04543 (0.620)	.054865 (0.551)
New	21.55266 (0.000)	21.85065 (0.000)	23.90555 (0.000)	24.526 (0.000)	24.61739 (0.000)
Constant	60.33125 (0.000)	60.12614 (0.000)	46.83549 (0.000)	46.13775 (0.000)	45.73628 (0.000)
R ²	0.1803	0.1823	0.3855	0.3946	0.3997

Note: the number between parentheses is the P-value

Figure 2.2: Screenshot taken from Eddhir (2009). Presented here as an example of a research paper which reports exact p-values. The circled p-values are the ones that are used in the analysis. Note: caption below table should read “the numbers shown in parentheses are p-values”.

In contrast, Figure 2.3 provides significance information only through star symbols (*, **, or ***), representing p-value intervals. In this example, the dependent variable is a binary variable representing auction success, with higher reputation scores expected to increase the probability of auction success.

TABLE 3 Regression Results of eBay Watch Data

Dependent Variables	= 1 if Complete the Auction Probit (coefficients)		ln(winning price/low book price) Controlling for Propensity Scores (coefficients)	
= 1 if graded	2.286 (1.261)	*	1.813 (.291)	***
= 1 if graded below 9		.202 (.337)		.308 (.107) ***
= 1 if graded 9		.268 (.357)		.159 (.112)
= 1 if graded 10		.223 (.376)		-.398 (.133) ***
= 1 if ungraded with no self-grade	2.417 (1.205)	**	1.740 (.277)	***
Seller self-grade * ungraded	.248 (.137)	*	.212 (.031)	***
= 1 if self-grade 9 * ungraded		.033 (.283)		.334 (.068) ***
= 1 if self-grade 10 * ungraded		.769 (.378)	**	.511 (.081) ***
ln(seller ratings+1) * graded	.084 (.049)	<u>*</u>	.097 (.049)	<u>**</u> -.026 (.017)
= 1 if any negative ratings * graded	.099 (.158)		.097 (.159)	-.015 (.050)
ln(seller ratings + 1) * ungraded	.178 (.058)	***	.169 (.052)	*** -.018 (.015)
= 1 if any negative ratings * ungraded	-.649 (.226)	***	-.683 (.222)	*** -.008 (.057)
= 1 if scanned picture is clear	.307 (.140)	**	.357 (.150)	.031 (.046)
= 1 if scanned picture is unclear	.757 (.235)	***	.714 (.233)	*** -.089 (.073)
= 1 if the seller claims to be a card dealer	-.146 (.170)		-.202 (.173)	.015 (.049)
Predicted probability of sale			.339 (.411)	.318 (.426)
Observations	1124		1124	778
R ²	.461		.463	.167
				.392

Notes: All regressions control for a full set of card identity dummies, payment methods, shipping options, length of auction, whether the auction ended on a weekend, whether the auction ended in prime time, whether there was a public or secret reserve price, and whether there was a Buy-It-Now option. The number of observations in the price regression is less than the total number of completed auctions, because Beckett Baseball Monthly does not report book prices for some cards graded below 8 (due to low trading volume). Fluctuation of card value is controlled by Beckett low book price (by card-month). Standard errors are in parentheses. *** $p < .01$, ** $p < .05$, * $p < .1$, two-tail.

Figure 2.3: Screenshot taken from Jin and Kato (2006). Presented here as an example of a published article which reports “stars” to represent significance levels. The underlined stars are the ones that are used in the analysis.

Figure 2.4 illustrates the process of collecting p-value data for this study, divided into two parts. In the top section, raw p-values are displayed. If the article reports an exact p-value, it appears here as a red star. If the article instead reports significance levels using symbols (*, **, or ***), these imply ranges of p-values which are depicted by the blue, green, and orange line segments, respectively. In the bottom section, transformed p-values ($-\log(p\text{-value})$) are shown. The exact p-values are transformed accordingly and displayed as red stars, reflecting their new positions

after the $-\log$ transformation. The same color scheme as in the top section is maintained for the significance symbols (*, **, and ***), but their positions differ due to the transformation applied. Note that if the information provided is ***, this implies that the p-value is less than 0.01, which in turn implies that $-\log(p\text{-value})$ is greater than 4.6. This amounts to a right-censored observation in estimation.

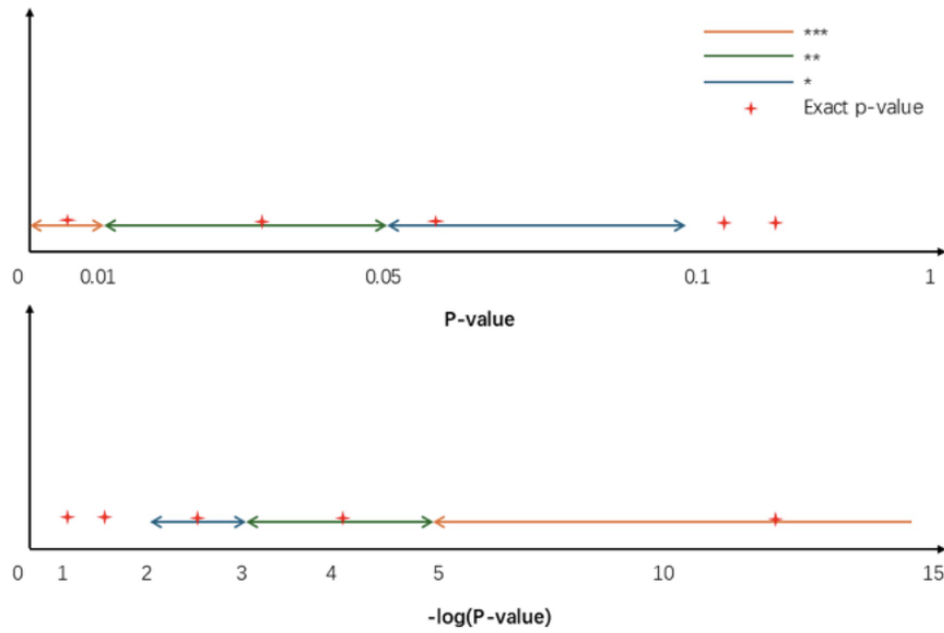


Figure 2.4: Illustration of how information on exact and interval p-values is transformed to obtain the dependent variable in the interval regression model.

2.4.2 Data Description

The dataset used in this study consists of variables gathered from multiple studies focusing on online e-WOM effects on customer behavior and selling performance in peer-to-peer online markets. The key variables include p-values, which indicate the statistical significance of the reported findings, and the sample size, representing the number of observations in each study.

Additionally, the dataset records the year each study was written and distinguishes between those written before and after 2020 through a dummy variable. Another important variable is the country category, which classifies the studies by their geographic focus (US, Asian countries, and European countries). The study

type is captured through a dummy variable differentiating between observational and experimental studies. Furthermore, the dataset covers research focus variables, including types of dependent variables such as customer purchase intention, final price, price premium, and sales volume, as well as independent variables like overall rating scores, positive reviews, and negative reviews. These variables form the foundation for the analysis conducted in this research.

Table 2.1: Variable Description

Variable	Definition
p-values	Reported p-values (transformed as $-\log(\text{p-value})$ in the main analysis).
log (sample size)	Log-transformed number of observations used in each study.
Publication after 2020	Dummy variable indicating publication time: 0 = before 2020, 1 = after 2020.
Country	Dummy variable for the study's geographic focus: 1 = US (reference group), 2 = Asian countries, 3 = European countries.
Research method	Dummy variable for the research method: 0 = Observational study (reference group), 1 = Experimental study.
Research focus 1	Dummy variable for the type of dependent variable: 1 = Customer purchase intention (reference group), 2 = Final price, 3 = Price premium, 4 = Sales volume.
Research focus 2	Dummy variable for the type of independent variable: 1 = Overall rating score (reference group), 2 = Positive reviews, 3 = Negative reviews.

Table 2.2 presents the descriptive statistics of the main variables used in the analysis. The variables include the log-transformed upper and lower p-values, country of focus, publication time (before or after 2020), study type, sample size (log-transformed), and research focus. The table shows the number of observations, mean values, standard deviations, as well as the minimum and maximum values for each variable. This provides a clear overview of the dataset and helps to understand the range and distribution of the key variables used in the regression analysis.

Table 2.2: Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Upper $-\log(\text{p-value})$	755	3.00	2.34	0	13.83
Lower $-\log(\text{p-value})$	823	7.45	6.39	0.22	16.12
$\log(\text{sample size})$	835	6.45	2.18	2.64	14.93
Country	826	1.51	0.63	1	3
Research Method	836	0.11	0.32	0	1
Publication after 2020	836	0.03	0.18	0	1
Research focus 1	690	2.74	1.03	1	4
Research focus 2	766	1.90	0.81	1	3

Figure 2.5 compares the distributions of sample sizes and log-transformed sample sizes. The histogram on the left reveals a significant right-skewness in the raw sample size distribution, with most values concentrated near the lower end. This extreme skewness poses challenges for statistical modeling, as it prevents meaningful variation from being captured. Conversely, the log-transformed sample size results in a more symmetric and approximately normal distribution, which is more suitable for regression analysis. By applying a log transformation, the skewness is mitigated, facilitating more accurate interpretation of the coefficients and allowing for better comparability across studies with varying sample sizes. As such, the log-transformed sample size was used in the analysis, as it more effectively represents the underlying data distribution and enhances the robustness of the statistical models by reducing the influence of extreme values.

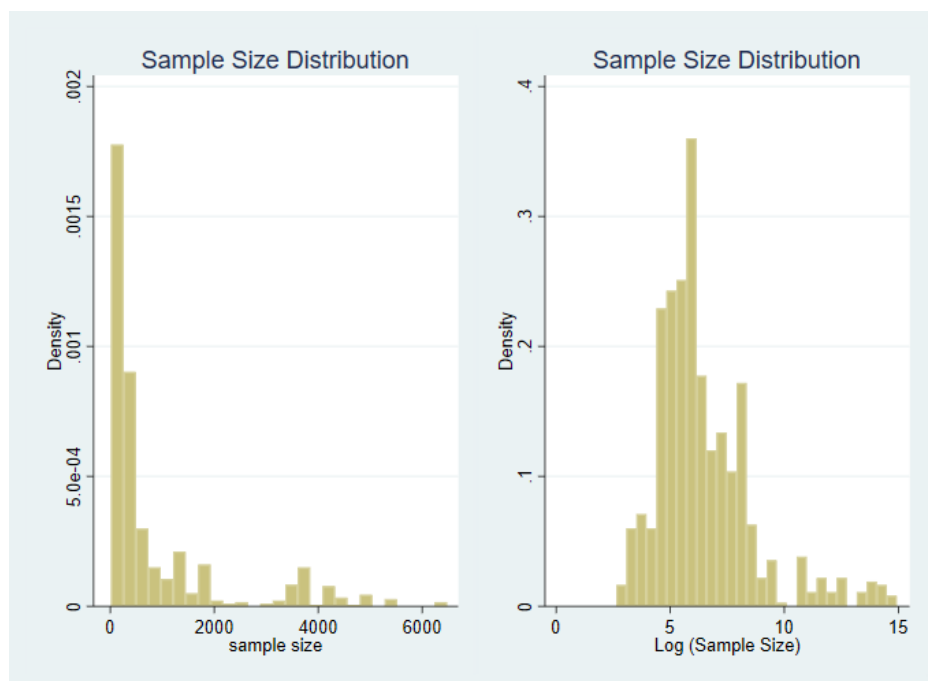


Figure 2.5: sample size distribution

Figure 2.6 illustrates the relationship between the log-transformed sample size and the negative log-transformed p-values. The red dots represent exactly reported p-values, while the blue intervals indicate studies that did not report exact p-values, but instead provided symbols such as *, ** and ***. Since the p-values are less than 1, their logarithmic transformation results in negative values, and by taking the negative of the log-p-value, all the red dots and blue intervals become positive. The upward-sloping green lowess curve is expected because larger sample sizes are associated with smaller p-values, indicating higher statistical significance. Recall from Section 2.3 that this positive relationship simply confirms that eWOM has an overall positive effect on the outcomes considered. Note also that the graph shown in Figure 2.6 is analogous to Figures 2.1b and 2.1c from Monte Carlo experiments performed in Section 2.3.

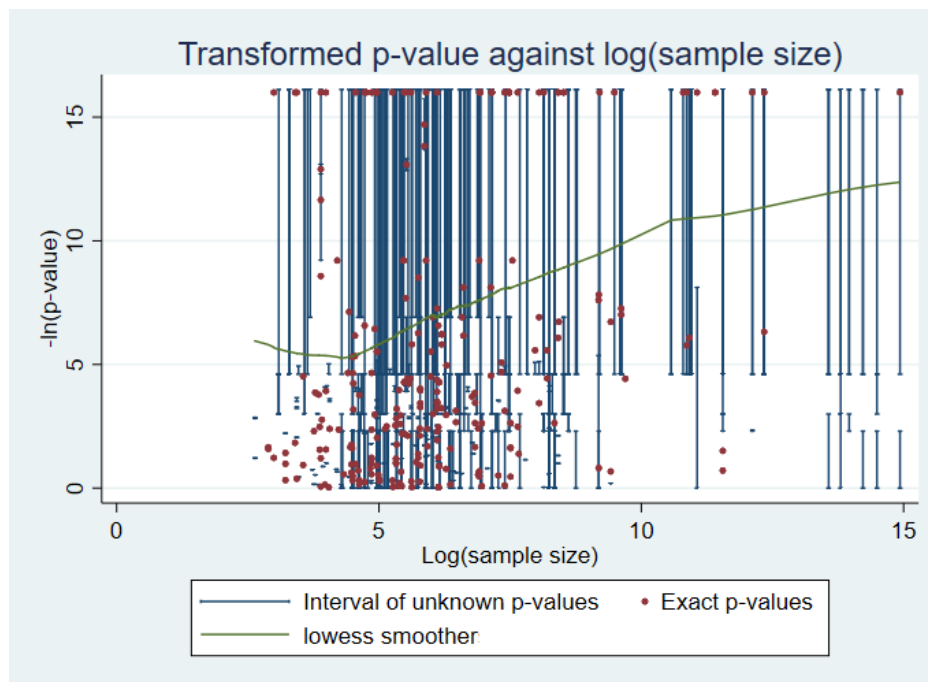


Figure 2.6: Transformed p-value against $\log(\text{sample size})$. Lowess smoother superimposed.

2.5 Methodology

This study employs a meta-regression analysis to explore broader patterns in research on online reputation (eWOM) effects. Unlike traditional meta-analyses, which typically compare similar types of data or studies—such as prior eWOM meta-analyses focusing either on customer purchase intention using experimental data or seller sales performance using field data—our study encompasses a more diverse range of research. Specifically, our dataset includes studies utilizing both experimental and field data, as well as studies examining various aspects of eWOM effects, including its influence on product sales, price premiums, positive eWOM impact, and negative eWOM impact. Given this heterogeneity, it is challenging to directly compare effect sizes across studies in a conventional meta-analysis.

To address this issue, we utilize p-values as the dependent variable across studies, providing a standardized measure for evaluating statistical significance. This approach allows us to systematically assess how eWOM influences customer purchase intention, actual purchase behavior, and seller performance across diverse research contexts. Additionally, meta-regression analysis enables us to identify key moderating factors that shape eWOM's impact, offering deeper insights into its role in digital commerce. By applying this methodology, we ensure a more comprehensive and robust evaluation of eWOM effects across various study designs and research

objectives.

Sample size is used as a control variable because larger samples typically yield more significant results due to reduced standard error. The regression results confirm this expectation, showing a significant negative correlation between sample size and p-value, underscoring the importance of accounting for sample size in meta-analyses.

2.5.1 Meta-Regression Analysis

This study employs two meta-regression approaches, guided by the foundational work of Loughin (2004) and inspired by subsequent research from Aliyu (2010). Loughin’s comprehensive examination of methods for combining p-values in meta-analysis serves as an authoritative reference, as it systematically compares techniques for integrating p-values from multiple studies, particularly when data sources vary in reporting formats. Loughin’s study emphasizes the importance of addressing heterogeneity across studies, which is crucial when some report exact p-values while others indicate significance levels through symbols like *, **, and ***. This work provides essential insights into ensuring robust and reliable cross-study comparisons in meta-analyses.

Building upon these concepts, our study adopts both a random effects probit model and a random effects interval regression model to analyze the mixed reporting formats found in eWOM research. The probit model simplifies statistical significance into a binary outcome (e.g., significant vs. not significant) and serves as a preliminary or taster analysis to provide an initial overview of patterns in the data. However, it does not make full use of the available information. In contrast, the interval regression model is selected as the primary analytical framework because it directly accommodates the interval-censored nature of many reported p-values. Specifically, many studies do not report exact p-values but instead use symbols to indicate significance levels (e.g., * for $0.05 < p < 0.1$, ** for $0.01 < p < 0.05$, *** for $p < 0.01$). Interval regression allows these data to be modeled appropriately, leveraging the additional information about significance strength that is lost in a simple binary framework. This approach enables a more precise and informative examination of how study characteristics relate to statistical significance in eWOM research.

2.5.2 Random-Effects Probit Model

We start with a model that sets out to identify the characteristics of a study that make it more or less likely to find a significant effect, where significance is simply treated as a binary variable (1 if test gives significant result; 0 otherwise). This binary variable is generated directly from the p-value, as being 1 if the p-value is less than 0.05, and 0 otherwise.

Given that the outcome is binary, and in order to account for study-specific unobserved heterogeneity, the random effects probit model is used. This model has previously been used for similar purposes by Aliyu (2010). The model can be written as:

$$\begin{aligned} \Pr(\text{significant}_{it} = 1) &= \Phi\left(\beta_0 + \beta_1 \cdot \log(\text{Sample size}_{it}) + \beta_2 \cdot \text{country}_i \right. \\ &\quad \left. + \beta_3 \cdot \text{publication 2020}_i + \beta_4 \cdot \text{Purchase Intent}_i \right. \\ &\quad \left. + \beta_5 \cdot \text{Research focus 1}_i + \beta_6 \cdot \text{Research focus 2}_i + u_i\right) \\ u_i &\sim N(0, \sigma_u^2) \end{aligned} \tag{2.2}$$

Where:

- i is for study i , and t is for test t .
- $\Phi(\cdot)$ denotes the standard normal cumulative distribution function (CDF).
- significant_{it} is the binary variable taking the value 1 if test t in study i shows a significant result.
- u_i captures the study-level random effects, accounting for unobserved heterogeneity between studies.

While the random effects probit model is a useful model to start with, it is not making use of all the available information. The available information not only indicates whether the test result is significant, but also includes a measure of the strength of significance in the form of a p-value or an interval of p-values. To capture this information, an interval regression model is required.

2.5.3 Random Effects Interval Regression

To address the limitations of the probit model, a random effects interval regression model was employed. This model allows for the analysis of interval-censored data,

which is critical for studies that do not report exact p-values but rather use significance ranges. The interval regression model treats the p-value as an interval, capturing both the upper and lower bounds of significance. This approach is particularly useful in meta-analyses, where exact p-values are not always available. The interval regression was developed by van Doorslaer and Jones (2003), self-reported health condition; Piekkola (2004), Wages and Collective Bargaining; and Shen (2008), WTP for eco-labelled products. Interval regression allows us to estimate relationships between independent variables and a latent variable, constrained within the reported upper and lower bounds of the p-values.

2.5.3.1 Log Transformation of p-values

Since p-values are always range between 0 and 1, taking the log of a p-value (i.e., $\log(p)$) results in a negative number. For instance, if the p-value is 0.01, then $\log(0.01) = -2$. Smaller p-values yield larger negative values. To maintain the interpretability of the results, we further apply a negative log transformation, denoted as $-\log(p)$, to ensure that smaller p-values correspond to larger positive values.

Justification for using $-\log(p\text{-value})$ transformation:

- **Positive values for easier interpretation:** By applying the negative log transformation, we convert the negative log values into positive numbers. This makes the regression results easier to interpret, as larger positive values correspond to smaller p-values, reflecting greater statistical significance.
- **Normalization of distribution:** The log transformation helps normalize the distribution of p-values, which is typically skewed with most p-values being small fractions. This improves the fit of the regression model by linearizing relationships that may be nonlinear in the original scale.

The interval regression model therefore uses the transformed $-\log(p)$ values as the dependent variable, where the intervals represent the ranges of p-values reported in the studies. This approach allows us to estimate the effects of the independent variables on the transformed p-values while retaining the interpretability and statistical validity of the results.

2.5.3.2 Random-Effects Interval Regression Model

$$\begin{aligned}
-\log(p\text{-value})_{it}^* &= \beta_0 + \beta_1 \cdot \log(\text{sample size})_{it} + \beta_2 \cdot \text{country}_i \\
&\quad + \beta_3 \cdot \text{publication 2020}_i + \beta_4 \cdot \text{Purchase Intent}_i \\
&\quad + \beta_5 \cdot \text{Research focus 1}_i + \beta_6 \cdot \text{Research focus 2}_i \\
&\quad + u_i + \epsilon_{it} \\
\epsilon_{it} &\sim N(0, \sigma_\epsilon^2) \\
u_i &\sim N(0, \sigma_u^2)
\end{aligned} \tag{2.3}$$

Where:

- i is for study i , and t is for test t .
- Dependent variable: The dependent variable $-\log(p\text{-value})_{it}^*$ is a latent variable, and the observed data are the interval-censored p-values, represented by their log-transformed upper and lower bounds.
- $\log(\text{sample size}_{it})$ is the natural logarithm of the sample size used for test t in study i .
- Country: Dummy variables for country categories, with the United States as the reference group (1 = US, 2 = Asian country, 3 = European country).
- Publication time: Dummy variable for publication year, indicating whether the study was published after 2020 (0 = before 2020, 1 = after 2020).
- Research Method: Dummy variable representing the study design (0 = Observational, 1 = Experimental).
- Research focus: Dummy variables for different independent variables used in the study (1 = Overall rating score, 2 = Information of Positive review, 3 = Information of Negative review)
- u_i : Study-specific random effects, accounting for unobserved heterogeneity across studies.
- ϵ_{it} : The per-observation error term.

As explained above, observations in the data set are of different types: some are exact values of $-\log(p\text{-value})$; some consist of an interval of values for $-\log(p\text{-value})$; some are upper-censored, meaning that the upper limit of the interval is $+\infty$, this situation arising when the available information is the maximum number of stars. The STATA “intreg” command is highly useful in this situation because it allows for all of these types of observation. Furthermore, the STATA “xtintreg” command extends the model to a random-effects version for panel data.

2.6 Results

Table 2.3: Random effects probit regression results with dependent variable: one if upper p-value less than or equal to 0.05; zero otherwise.

VARIABLES	(1)	(2)
log (sample size)	0.174*** (0.046)	0.166*** (0.046)
Asian ^a	0.1550 (0.215)	0.204 (0.212)
European ^a	0.592 (0.371)	0.581 (0.373)
Publication after 2020 ^b	-0.494 (0.828)	0.00717 (0.650)
Experimental ^c		0.953** (0.433)
Customer purchase intention ^d	1.252 (0.679)	
Final price ^d	-0.296 (0.202)	
Price premium ^d	-0.827 (0.584)	
Sale volume ^d	-0.170 (0.198)	
Positive reviews ^e	-0.317** (0.162)	-0.318** (0.162)
Negative reviews ^e	-0.495*** (0.172)	-0.496*** (0.172)
σ_u	0.737	0.754
Constant	-0.631* (0.347)	-0.814** (0.342)
Number of Observations	759	759
Number of Studies	134	134

^a *Country*: Reference group (1) = US, 2 = Asian country, 3 = European country.

^b *Publication after 2020*: Reference group (0) = before 2020, 1 = after 2020.

^c *Research method*: Reference group (1) = Observational, 2 = Experimental.

^d *Research Focus 1*: Dummy variable for Dependent variables; Reference group (0) = Customer purchase intention, 1 = Customer buying intention, 2 = Final price, 3 = Price premium, 4 = Sale volume.

^e *Research focus 2*: Dummy variable for Independent variables; Reference group (1) = Overall rating score, 2 = Positive review, 3 = Negative review

Note: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 2.3 reports the results from the random-effects probit model described in Section 5.2. This model provides an initial overview of factors influencing the likelihood of reporting a statistically significant p-value ($p \leq 0.05$) in studies on

online reputation. While not the core result of this study, it offers a basic perspective on significance patterns within the dataset. The positive association between $\log(\text{sample size})$ and statistical significance aligns with expectations, reflecting the greater power associated with larger samples. Experimental studies and studies examining positive or negative reviews, relative to overall rating scores, are more likely to report significant results. Regional and post-2020 publication effects are not statistically significant in this model.

Table 2.4: Random effect interval regression results with dependant variable: $-\log(p\text{-value})$

VARIABLES	(1)	(2)
log (sample size)	0.377*** (0.0775)	0.385*** (0.0824)
Asian ^a	0.608* (0.352)	0.687* (0.370)
European ^a	0.981* (0.580)	0.888 (0.619)
Publication after 2020 ^b	-3.455*** (1.049)	-1.980** (0.915)
Experimental ^c		3.110*** (0.657)
Customer purchase intention ^d	4.184*** (0.867)	
Final price ^d	-0.598* (0.344)	
Price premium ^d	-1.522* (0.905)	
Sale volume ^d	-0.170 (0.338)	
Positive reviews ^e	-0.782*** (0.264)	-0.818*** (0.264)
Negative reviews ^e	-0.910*** (0.270)	-0.919*** (0.272)
σ_u	1.217*** (0.189)	1.394*** (0.182)
σ_ϵ	2.059*** (0.074)	2.045*** (0.0734)
Constant	1.812*** (0.578)	1.355** (0.608)
Uncensored	89	89
Left-censored	0	0
Right-censored	188	188
Interval-censored	402	502
Observations	679	679
Number of studies	131	131

^a *Country*: Reference group (1) = US, 2 = Asian country, 3 = European country.

^b *Publication after 2020*: Reference group (0) = before 2020, 1 = after 2020.

^c *Research method*: Reference group (1) = Observational, 2 = Experimental.

^d *Research Focus 1*: Dummy variable for Dependent variables; Reference group (0) = Missing values, 1 = Customer buying intention, 2 = Final price, 3 = Price premium, 4 = Sale volume.

^e *Research focus 2*: Dummy variable for Independent variables; Reference group (1) = Overall rating score, 2 = Positive review, 3 = Negative review

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 2.4 presents the results from the random-effects interval regression model,

the primary analytical framework for this study. This model accommodates both exact and interval-censored p-values, allowing for a more nuanced examination of how study characteristics influence the strength of statistical significance as measured by $-\log(\text{p-value})$. The analysis reveals that larger sample sizes and experimental designs are associated with stronger statistical significance. Studies conducted in Asian countries, and to a lesser extent in Europe, tend to report stronger significance compared to US studies. Conversely, studies published after 2020 report weaker significance, suggesting potential shifts in the detectability of eWOM effects over time. Studies focusing on purchase intention yield stronger significance, while those examining final price or price premium yield weaker significance. Positive and negative reviews both contribute to stronger significance relative to overall ratings, with negative reviews exerting a larger effect.

2.7 Discussion

The findings from the interval regression analysis reveal several key insights into the conditions under which eWOM effects are statistically detectable and practically meaningful. First, regional variation plays a significant role in shaping eWOM effectiveness. Studies conducted in Asian countries report significantly stronger statistical significance than those in the United States, and European studies also show a positive, though somewhat less consistent, trend. These results suggest that consumer responsiveness to eWOM may differ based on cultural norms or market structures—such as trust in peer communication or digital literacy. From a managerial perspective, this implies that eWOM strategies may be more impactful in certain cultural contexts and should be tailored accordingly.

Second, the analysis underscores a meaningful distinction between studies focusing on customer purchase intentions and those measuring actual purchasing behavior. Studies centered on purchase intention are associated with substantially stronger statistical significance. In contrast, those examining final price or price premium exhibit significantly weaker results. This gap reflects a well-documented phenomenon in behavioral research—the intention–behavior gap—where consumers’ expressed willingness to buy does not always translate into real-world actions. This distinction has both theoretical and practical implications. On the one hand, it questions the external validity of experimental studies that rely on attitudinal measures; on the other, it reminds practitioners that influencing consumer attitudes may not be sufficient for driving concrete transactions.

The findings also show that experimental studies are more likely to report statistically significant results than observational studies. This is unsurprising, as experiments often control for confounding variables and allow for cleaner identification of causal effects. However, while this enhances internal validity, the generalizability of such findings may be limited in uncontrolled, real-world environments. Therefore, future research should continue to explore the trade-off between methodological rigor and ecological validity.

Temporal effects are also evident in the data. Studies published after 2020 tend to show significantly weaker eWOM effects. This decline may reflect growing consumer skepticism toward online reviews, driven by rising concerns about fake content, automated review generation, or platform manipulation. In the wake of the COVID-19 pandemic and the rapid expansion of digital commerce, consumers may have become more discerning, less trusting, or simply overwhelmed by the volume of user-generated information. For platforms and businesses, this finding reinforces the importance of investing in credible, transparent, and trustworthy review ecosystems.

Finally, the types of eWOM studied also matter. Both positive and negative reviews are associated with stronger significance relative to overall ratings, with negative reviews exerting a larger influence—consistent with theories of negativity bias. However, despite their statistical significance, the real-world effect sizes implied by these variables may be modest. The use of $-\log(p)$ as a dependent variable enables standardized comparisons across studies, but it does not measure economic magnitude directly. Thus, while this meta-regression identifies patterns in statistical reporting, future work incorporating effect size or elasticity estimates would be valuable in assessing the true market relevance of eWOM.

In summary, this study identifies several consistent factors—regional context, research design, review valence, and time period—that shape the detectability of eWOM effects. These results provide theoretical clarification and practical direction for optimizing eWOM strategy. To further bridge the gap between perception and behavior, future research should prioritize data that capture both purchase intention and actual behavior within the same sample, enabling a more direct test of eWOM’s capacity to convert consumer attitudes into economic action.

While this study focuses on statistical significance using $-\log(p)$ as a unified metric, it is important to emphasize that statistical significance does not

automatically translate into meaningful economic impact. One key reason for not using point estimates or standardized effect sizes is the substantial heterogeneity in outcome variables across the studies included in this meta-analysis. Some papers measure price premium, others focus on repurchase intention, while others examine willingness to recommend or actual sales volume. These outcomes are measured on different scales and units, making effect sizes inherently non-comparable. As such, p-values offer a consistent and interpretable indicator of whether an eWOM effect is detected, regardless of the underlying measurement framework.

To ensure conceptual coherence, this study also harmonizes the interpretation of significance across research designs. Specifically, a statistically significant effect of positive reviews is interpreted as indicating higher purchase intention or stronger market performance, while significant negative reviews suggest reduced consumer trust and lower expected outcomes. This alignment allows us to draw consistent insights from a diverse body of literature.

2.8 Limitation and future study

A key limitation of this study lies in the way it distinguishes between purchase intention and actual purchase behavior. Due to the lack of studies that report both outcomes on the same sample, we rely on the study's methodology as a proxy: experimental or survey-based studies are assumed to reflect purchase intention, while observational or field studies are interpreted as capturing actual behavior. Although this proxy approach is practical and aligns with existing literature, it is inherently imprecise. Future research would benefit greatly from datasets that include both behavioral intentions and observed purchasing outcomes for the same individuals. Such data would allow researchers to directly examine the intention-behavior gap and determine how far the influence of eWOM extends in the consumer decision-making process. Clarifying this distinction is particularly important in understanding the real economic impact of eWOM, and whether it translates into actual sales or remains at the attitudinal level.

It is also important to note that even highly statistically significant results—particularly those arising from large sample sizes—may not imply large or meaningful economic effects. The $-\log(p)$ framework used in this study allows for a standardized comparison of reported significance across heterogeneous studies, but does not quantify the magnitude of real-world impact. Future research should seek to

complement this approach with meta-analyses of standardized effect sizes or elasticity measures, where comparable outcome variables are available. Doing so would strengthen the connection between statistical detection and practical managerial or policy relevance.

While this study addresses potential publication bias by incorporating sample size controls and applying interval regression to account for imprecise significance reporting, such strategies may not fully eliminate concerns about selective reporting or p-hacking. To further examine this issue, we include two diagnostic figures in the Appendix—p-value distribution histograms (Figure 2.9a and Figure 2.9b) and a p-curve plot (Figure 2.10). The p-curve displays a left-skewed distribution with most p-values clustering near zero, which is typically interpreted as evidence of true underlying effects rather than selective reporting. Meanwhile, the p-value histograms show modest peaks around conventional thresholds (e.g., 0.05), but not to an extent suggesting pervasive p-hacking.

Additionally, Appendix Table 2.5 introduces an interaction term between sample size and research method (experimental vs. observational) to test whether significance levels are disproportionately driven by large-sample experimental studies—a pattern that may indicate publication bias. The interaction term is not statistically significant, indicating that while experimental designs yield stronger effects overall, this pattern is not amplified by sample size. Based on this combined evidence, we conclude that publication bias is likely limited in scope in our sample. Nevertheless, future work could extend the dataset to include unpublished manuscripts, working papers, and dissertations to further mitigate selective reporting and enhance the representativeness of meta-analytic conclusions.

2.9 Conclusion

This study provides a comprehensive meta-analysis of eWOM research, investigating how key factors, geographic differences, research methodologies, and publication timing affect its statistical significance. By comparing studies across diverse contexts, the research offers new insights into how eWOM shapes consumer trust, purchasing behavior, and business performance in an increasingly digital economy.

First, our analysis highlights significant regional variations in eWOM effectiveness. Studies conducted in Asia and Europe report stronger statistical

significance, suggesting that cultural and market-specific factors influence how consumers respond to eWOM. These findings have important implications for global digital businesses, as the role of eWOM in corporate reputation, transparency, and sustainability communication may vary across markets.

Second, this study integrates both purchase intention and actual sales metrics within a single meta-analytic framework, offering a richer understanding of eWOM's influence across the entire consumer decision-making process. Unlike prior meta-analyses that treat these outcomes separately, our approach reveals how eWOM can simultaneously shape attitudes and drive real market outcomes. This dual focus enables the identification of potential gaps between intention and action, which future research could explore using datasets that link individual-level intentions with actual purchase behavior. Such work would clarify whether intentions reliably predict actions in digital commerce, particularly in eWOM-driven contexts.

Third, our examination of methodological differences shows that experimental studies tend to report stronger effects, likely due to greater control over confounding variables. By contrast, observational studies, while capturing real-world behavior, may be influenced by external factors such as competitive pricing, platform algorithms, and consumer preferences. This underscores the need for robust, context-sensitive methodologies to accurately assess eWOM's impact.

Finally, we observe a decline in the statistical significance of eWOM effects in post-2020 studies. This trend may reflect shifts in consumer trust following the COVID-19 pandemic, during which online shopping expanded rapidly alongside concerns about fake reviews, rating manipulation, and unethical business practices. These developments raise critical questions about digital governance, corporate social responsibility (CSR), and the long-term sustainability of eWOM as a trust-based mechanism. Businesses must therefore invest in transparent review systems, AI-driven fraud detection, and ethical eWOM management to maintain consumer confidence.

2.10 Appendix

2.10.1 Data Sources

#	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T
1	abbr	study id	data id	product type	country	transaction type	market place	study type	model	N	DV	eff1	coe	LOWER P	UPPER P	s.e.	t-test	age	gender	edu
2	Ahidiari et al. (2015)			mixed	US	2	online retailer	2	table 4-1	247	CIB positive feedback	0.72	0.72	#NAME?	#NAME?		3.55			
3	Mahmud, MS, et al. (2020)			mixed	Bangladesh		social media	2		218	ing intention(CBI)	general	0.897	0.019	0.019					
4	Nunes, RH, et al. (2018)			Baby product	South America		social media	2		204	CBI uasive messages	general	0.73	0	0.001					
5	Yeon, J., et al., (2019)						social media	2		323	CBI systematic factors	general	0.471	0	0.001					
6	Yeon, J., et al., (2019)						social media	2		323	ual purchase (AP)	heuristic factors	0.124	0.09	0.09					
7	Yeon, J., et al., (2019)						social media	2		323	CBI heuristic factors	general	0.146	0.12	0.12					
8	Yeon, J., et al., (2019)						social media	2		323	AP systematic factors	general	0.025	0.773	0.773					
9	Moslehpour, M, et al. (2020)			Beauty product	Mangolia		social media	2		530	CBI	general	0.136	0	0.001					
10	Sharma, S(2021)			Hotel	Indian		Airbnb	2		325	CBI	general	-0.403	0.001	0.01		-8.203			
11	Sharma, S(2019)			Ride sharing service	India		Social media	2		325	CBI	general	-0.329	0.001	0.1		6.308			
12	Herseyawati, E., et al., (2021)			Energy drink	Indonesia		Social media	2		214	CBI	general	0.103	0.918	0.918					
13	Lin, SC(2021)						online retailer	2		839	CBI	general	0.259	0	0.001		6.986			
14	Friedrich, T(2020)				Asian(china)		online retailer	2			CBI	general								
15	Bilal, M., (2021)				China		social media	2		477	CBI	general	1.32	0	0.001					
16	Madzunya, N., et al(2021)			Luxury good			social media	2		364	CBI	general	0.906	0.0001	0.0001		16.173			
17	Kunja, SR., (2021)			Hedonic			social media	2		326	CBI	general	0.1641	0.0323	0.0323					
18	Kunja, SR., (2021)			Utilitarian			social media	2		326	CBI	general	0.0458	0.0193	0.0193					
19	mad, W. & Zhang, QY., (2020)			green product	China		social media	2		1002	CBI	general	0.004	0.514	0.514		0.653			
20	Ardyan, E(2021)			Covid product	Indonesia		online retailer	2		691	CBI negative ewom	general	-0.213	0	0.001					
21	Sharma, D., et al. (2021)			fashion	India		online retailer	2		708	CBI	general	0.242	0	0.001		6.581			
22	Palalic, R.,(2020)				Pakistan		social media	2		396	CBI	general	0.153	0.011	0.011		2.557			
23	Akram, U., (2021)			Hedonic	China		social media	2		585	CBI	general	0.512	0	0.001					
24	Akram, U., (2021)			Utilitarian	China		social media	2		585	CBI	general	0.619	0	0.001					
25	Sokolova, K & Kefi, H., (2020)			beauty product	France		social media	2		1209	CBI	general	0.346	0	0.001		10.655			
26	en, CC. & Chang, YC., (2018)			Hotel	USA		Airbnb	2		280	CBI rating (stars)	general	1.207	0.05	1					
27	en, CC. & Chang, YC., (2018)			Hotel	USA		Airbnb	2		280	CBI volume	general	2.453	0.01	0.05					
28	en, CC. & Chang, YC., (2018)			Hotel	USA		Airbnb	2		280	CBI perceived value	general	0.547	0	0.001					
29	Cheung, ML., et al(2021)			Hotel	Chinese		Online retailer	2		538	CBI Emotional value	general	0.114	0.007	0.007		2.461			
30	Cheung, ML., et al(2021)			Hotel	Chinese		Online retailer	2		538	CBI Functional value	general	0.283	0	0.001		5.927			
31	Cheung, ML., et al(2021)			Hotel	Chinese		Online retailer	2		538	CBI Relational value	general	0.322	0	0.001		6.994			
32	Cheung, ML., et al(2021)			Hotel	Chinese		Online retailer	2		538	CBI Entitativity value	general	0.162	0	0.001		3.895			
33	Cuesta-Valino (2022)			Small retailer	Spanish		Online retailer	2		4036	CBI	general	0.368	0.01	0.05					
34	SR & Acharyulu, GVRK (2018)			smart phone	India		social media	2		762	CBI	general	0.4	0	0.001		10.892			
35	Sijabat, DCS (2020)			wedding service	Indonesia		social media	2		100	CBI	general	0.284	0.01	0.05		2.125			
36	Javed, S (2021)			fashion product			social media	2		969	CBI	general	0.203	0	0.001		9.558			
37	Williams, D (2021)						social media	2		226	CBI	general	0.039	0.518	0.518		0.647			
38	Milakovic, IK (2020)				Croatian		social media	2		960	CBI	general	0.163	0.01	0.05					
39	Milakovic, IK (2020)				Croatian		social media	2		960	CBI	general	0.472	0.01	0.05					
40	Silva, AS(2021)			hotel	Brizal		online retailer	2		660	CBI	Reliability	0.441	0.01	0.05		1.071			
41	Silva, AS(2021)			hotel	Brizal		online retailer	2		660	CBI	Attractiveness	0.113	0.01	0.05		3.128			
42	Bobkowski, P.S. (2015)			household	US		social media	2		275	ITION TO SHARE	general	0.58	0	0.01	0.08	46.28	45	university	
43	Bobkowski, P.S. (2015)			Technology	US		social media	2		270	ITS	general	0.28	0.012	0.012	0.11	46.28	45	university	
44	leung, C.M. & Lee, M.K. (2012)			publicgood	HK		social media	2		203	ITS	general	0.112	#NAME?	#NAME?		1.763	24	43	university
45	Choi, J.H. & Scott, J.E. (2013)				South Korea		social media	2		221	Trust	general	0.51	#NAME?	#NAME?		10.02	27	17.5	university
46	elidou, N. & Argyriou, E. (2012)			experience product	Chinese		online retailer	2		106	CBI	general	1.26	0	0.001		25.8	44.3	university	
47	elidou, N. & Argyriou, E. (2012)			experience product	UK		online retailer	2		103	CBI	general	0.92	0	0.001		31.3	51.5	university	
48	elidou, N. & Argyriou, E. (2012)			search product	Chinese		online retailer	2		106	CBI	general	0.88	0	0.001		25.8	44.3	university	
49	elidou, N. & Argyriou, E. (2012)			search product	UK		online retailer	2		103	CBI	general	1.08	0	0.001		31.3	51.5	university	
50	Chu, S.C. & Kim, Y. (2011)				US		social media	2		363	ITS	general	0.13	0.01	0.05		21	46.6	university	
51	Chu, S.C. & Kim, Y. (2011)				Chinese		social media	2		300	ITS	general	0.23	0	0.001		22	48.7	university	
52	uezaul, S. & McLeay, F. (2015)			travel	UK		social media	2		49	Trust source credibility	general	0.07	#NAME?	#NAME?		1.049	25	53.3	university
53	uezaul, S. & McLeay, F. (2015)			travel	UK		social media	2		49	Trust nformation quality	general	0.402	#NAME?	#NAME?		4.966	25	53.3	university
54	uezaul, S. & McLeay, F. (2015)			travel	UK		social media	2		49	Satisfaction nformation quality	general	0.402	#NAME?	#NAME?		5.392	25	53.3	university
55	uezaul, S. & McLeay, F. (2015)			travel	UK		social media	2		49	Trust Web quality	general	0.279	#NAME?	#NAME?		4.036	25	53.3	university
56	uezaul, S. & McLeay, F. (2015)			travel	UK		social media	2		49	CBI Trust	general	0.63	#NAME?	0.0001		9.148	25	53.3	university
57	Shao, J. & Wang, W. (2013)			travel	China		social media	2		549	Trust	general	0.732	0	0.001		26	46	university	
58	Shao, J. & Wang, W. (2013)			travel	China		social media	2		549	Trust	quality	0.19	0	0.001		26	46	university	
59	Shao, J. & Wang, W. (2013)			travel	China		online retailer	2		549	CBI	general	0.353	0	0.001		26	46	university	
60	Shao, J. & Wang, W. (2013)			travel	China		online retailer	2		549	CBI	quality	0.223	0	0.001		26	46	university	
61	Zhou, Z. & Zhao, D.T. (2010)				China		social media	2		240	CBI	general	0.54	#NAME?	0.0001		10.11	23	77.1	university
62	Zhou, Z. & Zhao, D.T. (2010)				China		social media	2		240	CBI	quality	0.14	#NAME?	#NAME?		2.48	23	77.1	university
63	ee, J.N. and Tan, B.C.Y. (2013)			daily product	Korea		Social media	2		326	Loyalty number of review	general	-0.029	0.4	0.4	0.035	-0.843	38	50	university
64	ee, J.N. and Tan, B.C.Y. (2013)			daily product	Korea		Social media	2		326	Loyalty compactness	general	0.087	0.018	0.018	0.037	2.374	38	50	university
65	ee, J.N. and Tan, B.C.Y. (2013)			daily product	Korea		Social media	2		326	Loyalty adequacy	general	0.078	0.038	0.038	0.037	2.088	38	50	university
66	ng, J.C. and Chu, Y.P. (2015)				Taiwan		Social media	2		659	CBI	general	0.06	0.01	0.05		2.05	21	46.4	university
67	ng, J.C. and Chu, Y.P. (2015)				Taiwan		Social media	2		659	CBI	quality	0.15	0.01	0.05		3.57	21	46.4	university
68	Simon, J. and Kiss, V. (2017)				Hungary		Social media	2		1000	Satisfaction	general	0.317	0	0.001			47	43.5	highschool
69	Akyuz, A. (2013)			electronic product	Turkey		Social media	2		251	CBI credibility	general	0.3	#NAME?	#NAME?		4.911	30	42.2	university
70	Islam, S., & Sajjad, M. (2016)			electronic product	Pakistan		Social media	2		251	CBI	general	0.594	0.001	0.01	0.164	26	45.4	university	
71	ndari, M., & Rodgers, S. (2017)			electronic product	US		online retailer	2		447	CBI	general	0.31	0.01	0.05	0.11	18.75	29	university	
72	Chung, R. (2014)				HK		Social media	2		100	CBI	quality	0.68	#NAME?	0.001		14.21	24.9	university	
73	K. Q., & Thadani, D. R. (2009)			Watch	HK		online retailer	2		40	Trust	general	0.69	#NAME?	0.001		11.02		50	university
74	u, L.-C., & Huang, S.-C. (2013)			fashion	Taiwan		Social media	2		353	CBI	general	0.299	#NAME?	#NAME?		5.363	25	16.43	university
75	u, L.-C., & Huang, S.-C. (2013)			fashion	Taiwan		online retailer	2		353	CBI	general	0.266	#NAME?	#NAME?		4.982	25	16.43	university
76	E., & Molla-Descaals, A. (2015)				UK		online retailer	2		1533	CBI	quality	0.09	#NAME?	#NAME?		2.74		46.4	university
77	E., & Molla-Descaals, A. (2015)				UK		online retailer	2		1533	CBI	ease of use	0.077	#NAME?	#NAME?		2.61		46.4	university
78	Dowell, W., & Daffon, A. (2014)			travel	US		online retailer	2		142	CBI	quality	0.11	0.01	0.05	0.1	39.59	30	59.7	university

Figure 2.7: List of studies that I added to the original dataset.

2.10.2 Distribution of Reported p-values

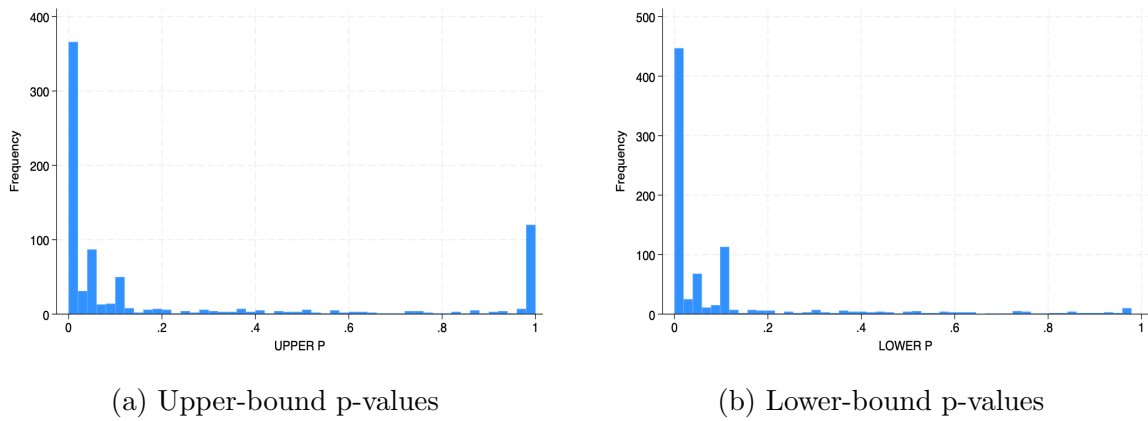


Figure 2.8: Histograms of upper and lower bounds of reported p-values.

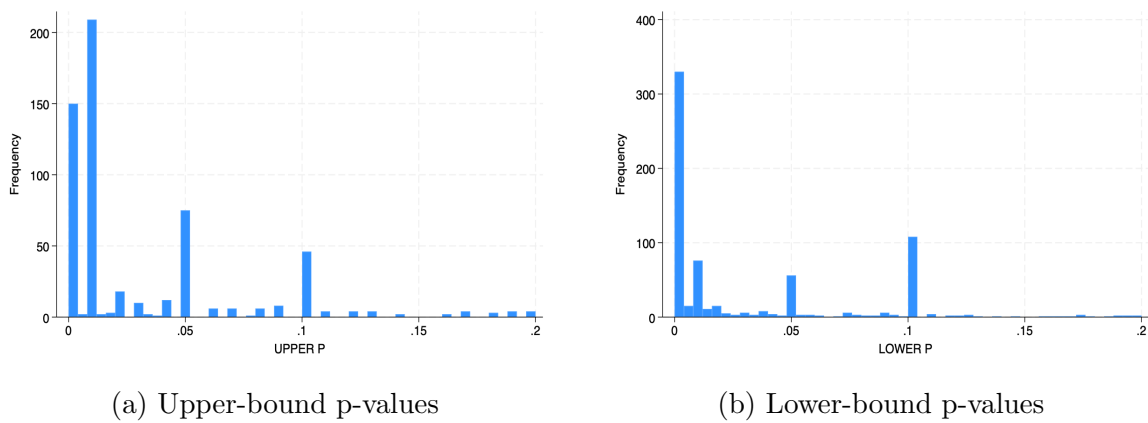


Figure 2.9: Histograms of Upper and Lower Bounds of Reported p-values (0–0.2).

2.10.3 P-curve distribution

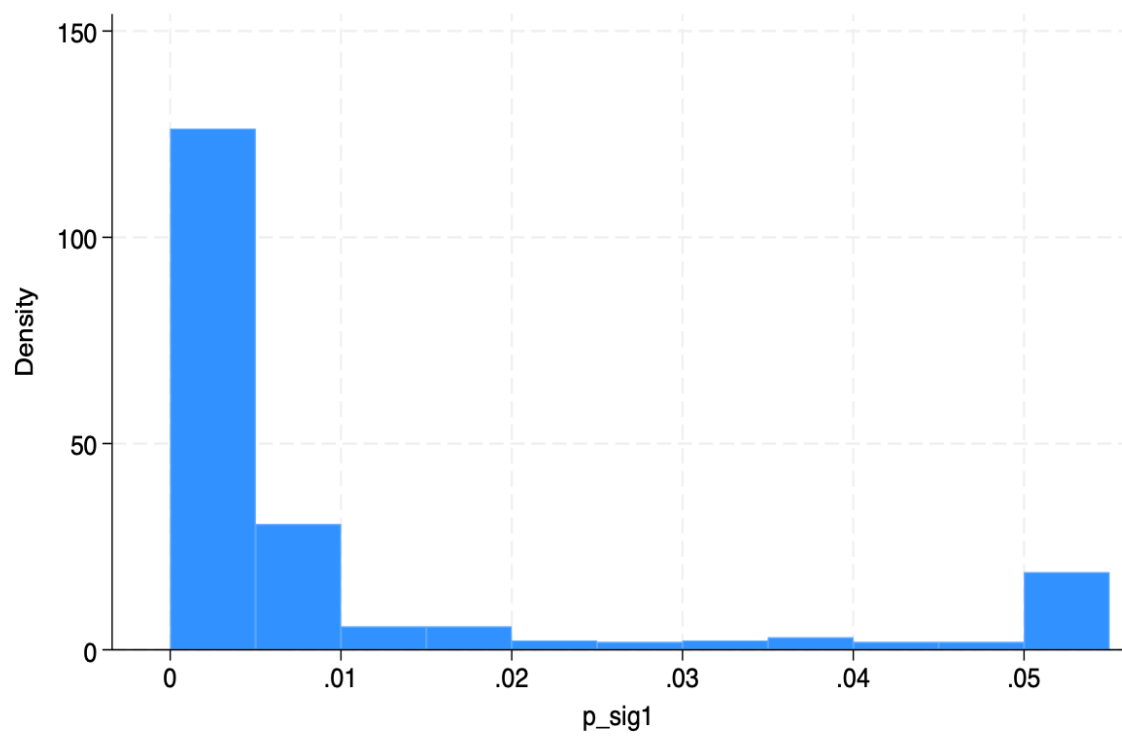


Figure 2.10: P-curve Distribution of Statistically Significant Results

Table 2.5: Random effect interval regression results with dependent variable: $-\log(p\text{-value})$

VARIABLES	(1)
log(sample size)	0.374*** (0.085)
Asian ^a	0.416 (0.403)
European ^a	0.893 (0.591)
Publication after 2020 ^b	-3.203*** (1.081)
Experimental ^c	-7.851* (3.998)
log(sample size) $\times$ Experimental ^f	-0.505 (0.673)
Positive reviews ^e	-0.732** (0.300)
Negative reviews ^e	-0.839*** (0.301)
σ_u	1.132*** (0.215)
σ_ϵ	2.057*** (0.084)
Constant	9.089** (3.961)
Uncensored	58
Left-censored	54
Right-censored	0
Interval-censored	438
Observations	550
Number of studies	110

^a *Country*: Reference group (1) = US, 2 = Asian country, 3 = European country.

^b *Publication after 2020*: Reference group (0) = before 2020, 1 = after 2020.

^c *Research method*: Reference group (1) = Observational, 2 = Experimental.

^e *Research focus 2*: Dummy variable for independent variables. Reference group (1) = Overall rating score, 2 = Positive review, 3 = Negative review.

^f *Interaction term*: log(sample size) $\times$ Experimental dummy.

Note: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Chapter 3

The Effect of Weather on Wine Prices

3.1 Introduction

Wine is an agricultural product uniquely suited to economic analysis in the context of climate change. Its price and quality are highly sensitive to local weather conditions, with variations in temperature and rainfall capable of producing dramatic shifts in market value—even among wines produced from the same grape variety and vineyard (Ashenfelter, 2010). In some cases, year-to-year price differences can exceed a factor of 20. Moreover, unlike most agricultural products, fine wine improves with age and is storable over long horizons, making it not only a consumption good but also an investable asset class (Fogarty, 2010; Masset and Weisskopf, 2010; Sanning et al., 2008). These features—climatic sensitivity, durability, and heterogeneity—make wine a revealing microcosm for understanding how climate risk translates into economic outcomes. Accordingly, the economic literature on viticulture has increasingly been used to anticipate the broader implications of climate volatility for agriculture, land use, and rural development.

Seminal work by Ashenfelter et al. (1995) demonstrated that the price of Bordeaux red wines could be predicted using a small set of weather variables from the growing season. His hedonic model challenged the dominance of expert scores and marketing narratives by showing that temperature, rainfall, and sunshine were strong predictors of wine quality and price. However, Ashenfelter’s analysis was geographically narrow, focusing on a single region and wine type within a uniform institutional and climatic setting. While this foundational research was highly influential, its generalisability across countries, varieties, and wine styles remains underexplored.

Historically, empirical research in wine economics has primarily focused on single-country or region-specific analyses, such as Bordeaux in France or California in the U.S. While such settings offer a clear institutional framework and relatively homogeneous growing conditions—allowing for precise identification of weather effects—they also present limitations. Most notably, they raise concerns about selection bias, as the findings may not generalize beyond the specific region studied. Furthermore, these analyses are vulnerable to country-specific shocks such as inflation, monetary policy shifts, or regulatory changes, which may confound the estimated effects.

By contrast, cross-country data, though more heterogeneous and potentially noisier, offers a way to mitigate these issues. The use of country fixed effects helps absorb time-invariant institutional differences, while the broader scope improves the external validity of findings. This approach also allows for the examination of

whether the climate–price relationship holds across different production systems and market structures. Thus, this study adopts a cross-national framework to test the generalizability of climate effects and to provide insights that are relevant for climate adaptation at the global scale.

The climatic variables studied include growing season temperature, growing season precipitation, maturation precipitation, and post-harvest (storage) precipitation. These are matched to wine price data from Wine-Searcher using the ERA5 climate archive, forming a comprehensive dataset for empirical analysis. Hedonic regression results show that growing season temperature and storage season rainfall significantly affect wine prices across countries and varieties. Specifically, higher growing-season temperatures are positively associated with wine value, while excess storage-period rainfall is detrimental—likely due to spoilage or suboptimal aging conditions.

This study contributes to the literature in three key ways. First, it demonstrates that the climate–price relationship found in Bordeaux can be extended to a wider range of production systems, supporting the robustness of Ashenfelter’s original insights. Second, it highlights the relevance of post-harvest climate effects, an area often neglected in prior studies. Third, by using cross-national data, it offers a comparative perspective that informs both producers and policymakers. This broader geographic coverage also helps bridge the research gap in underrepresented wine-producing regions and enables globally relevant insights on climate risk and pricing. The findings hold practical implications for growers, investors, and regulators seeking to adapt to climatic uncertainty in the global wine market.

3.2 Literature Review

Although this study focuses on the influence of seasonal weather conditions on wine prices, it is important to situate these short-term effects within the broader context of climate change. Existing literature widely agrees that global warming is expected to raise average temperatures worldwide, but its effects on precipitation patterns remain more uncertain. For instance, models predict that rainfall may increase in higher latitudes but decline in lower ones (Kelemen et al., 2009; Stocker, 2014). Due to these uncertainties, many climate–viticulture studies emphasize temperature over precipitation, despite the importance of both factors for grape development.

Several studies have shown that the anticipated effects of climate change on grape growing depend strongly on both the methodology used and the extent to which adaptation strategies are considered. Static suitability analyses, such as those by Hannah et al. (2013) and White et al. (2006), often predict severe losses for established premium regions like Bordeaux, Napa Valley, and Tuscany. Conversely, areas at higher latitudes, previously unsuitable for commercial viticulture, may benefit from warmer climates. However, the realization of such opportunities depends critically on regional adaptive capacity.

Importantly, Europe—home to many prestigious wine regions—is seen as less adaptable than New World producers. This is due in part to stronger institutional ties to geographic origin (e.g., through appellation laws) and regulatory constraints on vineyard relocation. As such, understanding how short-term weather conditions impact price outcomes across countries and vintages may offer useful insights for long-run climate adaptation—particularly in regions with limited flexibility.

This chapter contributes to this broader literature by empirically quantifying the effect of temperature and rainfall during distinct production phases—growing, maturation, and storage—on wine prices. While it does not directly model climate change, the analysis of observed weather variation offers indirect evidence on which stages and conditions are most economically sensitive, thereby informing risk management and adaptive strategies in the wine industry.

3.2.1 Temperature Effects on Wine Prices

Numerous empirical studies have reinforced the link between climatic variability and wine prices, particularly through changes in growing season temperatures. For example, Ashenfelter et al. (1995) demonstrate that a 1°C increase in average growing season temperature can raise Bordeaux wine prices by over 60%, highlighting the substantial economic sensitivity of fine wines to climate. Extending this analysis, Jones and Storchmann (2001) and Chevet et al. (2011) show that warming trends have increased both the frequency of high-quality vintages and the responsiveness of prices to temperature shocks. In other regions, the relationship appears nonlinear: Byron and Ashenfelter (1995) and Haeger and Storchmann (2006) find inverted U-shaped effects, indicating diminishing or even negative returns to temperature increases beyond optimal thresholds. Wood and Anderson (2006) provides further evidence of heterogeneous effects in Australia, with warmer regions

potentially facing declining prices due to excessive heat. In Germany's Mosel Valley, however, Ashenfelter and Storchmann (2010) find that warmer growing seasons significantly enhance both land values and wine revenues. Empirical agronomic research supports these findings by identifying the phenological window from budburst to *véraison* as the critical period during which temperature affects berry development and yield potential (Zhu et al., 2020). Furthermore, elevated temperatures during maturation influence sugar accumulation, acidity, and sensory profiles, which in turn affect quality perceptions and pricing (Sadras et al., 2012). These studies collectively underscore the importance of both average and extreme temperature conditions, with their economic impacts depending on varietal characteristics and regional climatic baselines.

3.2.2 Rainfall and Water Stress Effects

Rainfall also plays a critical role in shaping both yield and quality components of wine. Favorable rainfall patterns during the early growing season can enhance berry set and vine productivity, thereby increasing supply and potentially moderating prices (Ashenfelter et al., 1995). In contrast, excess rain during flowering or harvest can dilute grape quality or increase the risk of fungal diseases, negatively impacting perceived wine value. For instance, Zhu et al. (2020) find that rainfall before flowering influences berry development, while post-*véraison* precipitation tends to have limited yield effects but can affect flavour concentration and stability. Similar conclusions are reached by Yang et al. (2022) and Anastasiou et al. (2023), who emphasize that yield losses are more often due to early-season water stress than late-season droughts. These findings suggest that rainfall must be decomposed across phenological stages to accurately evaluate its heterogeneous economic effects. Moreover, the impact of rainfall interacts with other factors such as soil type, drainage capacity, and regional irrigation practices, complicating direct attribution of rainfall to pricing outcomes.

3.2.3 Other Determinants of Wine Prices

Beyond climate, a wide array of intrinsic and extrinsic characteristics influence wine pricing. These include geographical origin, grape variety, vintage year, winemaker reputation, and expert evaluations. Wines from prestigious regions such as Bordeaux often command substantial premiums due to historical quality, *terroir* characteristics, and regulatory protections (Ginsburgh et al., 2013; Cardebat and Livat, 2016). Varietals such as Cabernet Sauvignon and Pinot Noir are widely associated with higher perceived quality (Carew and Florkowski, 2008), and award-winning producers or brands with strong reputations can further elevate price levels through

trust-based signalling (Schamel, 2000; Gergaud and Ginsburgh, 2010). In international markets, expert ratings and vintage year declarations remain influential, shaping consumer perceptions of exclusivity and market segmentation (Jones and Storchmann, 2001; Combris et al., 1997). Quantitative studies such as Costanigro et al. (2007) and Haeger and Storchmann (2006) confirm that label features, critical acclaim, and regional identity are significant price determinants, particularly in the mid- to high-end segments. To clarify their roles, price determinants can be grouped into: (1) quantity-related factors such as growing season conditions affecting yield, (2) quality-related factors including maturation climate, varietal traits, and terroir, and (3) prestige-related factors like vintage year, producer brand, and expert scores. While this study focuses on weather and vintage variables, branding and packaging are excluded due to data limitations and their relatively minor role in the context of the present analysis.

3.2.4 HPM and quantile analysis

The Hedonic Pricing Model (HPM), originally introduced by Lancaster (1966) and formalized by Rosen (1974), posits that a product's price is determined by the bundle of its characteristics—both intrinsic and extrinsic. Consumers assign value to each attribute and are willing to pay a price that reflects their combined utility. This model is particularly well-suited for analyzing wine prices, as wine is a highly differentiated product whose value is shaped by observable features such as vintage, region of origin, and climatic conditions.

Compared to standard applications in urban economics—such as housing markets, where structural and locational attributes may be endogenous to price formation—this study benefits from the use of exogenous explanatory variables. Weather factors like temperature and precipitation are naturally occurring and not influenced by producer or consumer behavior, reducing the likelihood of simultaneity or omitted variable bias. This enhances the credibility of the causal inference drawn from the model.

The use of HPM in wine economics gained prominence with the work of Ashenfelter (2008), who demonstrated that a small set of growing-season weather variables could explain much of the price variation in Bordeaux wines. Although Ashenfelter did not label his approach as a hedonic model, it has since been widely interpreted as one. Building upon this foundation, a large body of literature has applied HPM to decompose wine prices into implicit values of characteristics such as

region, grape type, and producer reputation (Brentari et al., 2015; Galati et al., 2017; Rossetto and Galletto, 2019; Oczkowski, 1994; Combris et al., 1997; Benfratello et al., 2009; Di Vita et al., 2015; Oczkowski and Doucouliagos, 2015; Thompson et al., 2022).

Nonetheless, most existing studies have focused on single countries or regions, limiting the generalisability of their findings. This study addresses that gap by constructing a comprehensive panel dataset covering major wine-producing countries, including France, Italy, the United States, Spain, Austria, Germany, and Greece, and applying a consistent hedonic framework to test whether the relationship between climate conditions and wine prices holds across diverse institutional and environmental settings.

3.2.5 The contribution of Orley Ashenfelter

Orley Ashenfelter is one of the earliest scholars to use weather variables to predict wine prices. His research demonstrated that simple climate variables, such as average temperatures during the bud break and bloom periods (March to June), as well as rainfall during maturation (September/October) and the preceding winter dormancy period, could explain over 80% of the variability in Bordeaux wine prices (Ashenfelter et al., 1995). Although he did not explicitly refer to his model as a hedonic pricing model, his study has been widely cited in subsequent research applying hedonic models to wine prices. Ashenfelter's work not only highlighted the critical influence of climate on wine quality but also provided a strong foundation for future studies. Additionally, I discovered that this article was published three times in different journals (Ashenfelter et al., 1995; Ashenfelter, 2008, 2010), further underscoring the impact of his research.

3.3 Data

3.3.1 Data Source

3.3.1.1 Wine data

In this study, the price and vintage year of wines were scraped from the Wine-Searcher website in January 2023. The wine price reflects the current market value as listed on Wine-Searcher, with prices typically updated every three days, ensuring a close approximation of real-time market conditions. The mean price is calculated using a "topped and tailed" method, where the highest and lowest 20% of

prices are excluded to minimize distortion caused by outliers. This approach results in a more accurate and representative average price. All prices are standardized to a 750ml bottle equivalent and exclude taxes, ensuring consistency across the dataset.

The vintage year refers to the year in which the grapes were harvested and the wine was produced. Vintage year plays a significant role in wine pricing, as it reflects the unique weather conditions and growing environment of that specific year, which can have a major influence on the quality and desirability of the wine. This comprehensive approach to pricing and vintage ensures that the dataset provides a reliable foundation for analyzing the factors that influence wine prices in the current market

3.3.1.2 Weather data

For this study, weather data was obtained from the ERA5 ¹ monthly averaged data on a single-level dataset, provided by the Copernicus Climate Change Service (C3S). This dataset is accessible through the Climate Data Store (CDS) and spans from 1940 to the present. The ERA5 dataset offers comprehensive and high-resolution reanalysis data, which includes variables such as temperature, rainfall, and other climatic factors that are crucial for analyzing their impact on wine prices.

Specifically, the variables of interest were extracted as follows: rainfall data was collected for the growing, maturation, harvest, and storage seasons, providing essential insights into the influence of precipitation on different stages of grape development and wine production; temperature data was collected for the growing season and storage periods, recognizing the significant role temperature plays in grapevine physiology and the biochemical processes affecting wine quality.

The ERA5 dataset was selected due to its high temporal and spatial resolution, as well as its long-term consistency, making it an ideal source for analyzing climatic impacts over multiple decades. The data were accessed and downloaded via the Copernicus Climate Data Store interface, ensuring accurate and reliable input for the subsequent analysis.

¹For more information on the ERA5 dataset, visit <https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=form>.

3.3.2 Data Integration from Multiple Sources

In this study, the dataset used for analysis was constructed by combining two different sources of data. The wine data, including information on price and vintage year, was scraped from the Wine-Searcher website, while the weather data was sourced from the ERA5 monthly averaged dataset, provided by the Copernicus Climate Change Service (C3S). These two datasets were merged based on country ID and vintage year to create a cross-sectional dataset that captures the weather conditions corresponding to each vintage year alongside the respective wine prices. This integration allows for a comprehensive analysis of how climatic factors, such as temperature and rainfall, influence the pricing of wines across different regions and years.

3.3.3 Data Description

According to the wine-searcher website, their extensive database comprises price lists from 91,107 wine merchants globally. Remarkably, these prices are updated every three days, directly sourced from the sellers' websites. The calculation of the average price involves the following steps: firstly, all units and prices are standardized to a 750ml equivalent. Subsequently, the average prices are determined from a carefully curated data set, excluding the highest and lowest 20 percent of prices to avoid any potential skewing caused by pricing errors. In instances where a limited number of prices are available, the median is employed as a more reliable measure. This meticulous approach ensures the accuracy and reliability of the average price data provided by the website.

Table 3.1: Definition of Variables

Variable	Description
Price	Average sale price of the wine (Pounds per 750ml bottle)
year	Year of wine production
rain_mature	Total precipitation in the maturation months (mm)
rain_store	Total precipitation in the storage months (mm)
temp_growing	Average temperature in the growing months (K)
Wine_type	Dummy variable: 1 = red wine, 0 = white wine

For a more detailed explanation of the calculation methods for the weather variables, please refer to the Appendix.

The dependent variable in all models is the natural logarithm of the average sale price of wine. This transformation helps normalize the distribution of the price data

and allows for the interpretation of coefficients as elasticities, as illustrated in Figure 3.1.



Figure 3.1: Price distribution

The independent variables include the Vintage year and several climatic factors. As shown in Figure 3.2, the LOWESS plots illustrate the relationship between wine prices (in log form) and vintage year for both red and white wines from 1980 to 2020. For red wines, there is a clear downward trend in prices as the vintage year becomes more recent, with older vintages (particularly before 1995) commanding higher prices. This suggests that red wines gain market value with age, likely due to perceived improvements in quality or rarity. Similarly, white wines show a decline in prices for more recent vintages, although their prices appear to start lower than those of red wines, especially for older vintages. The decline in white wine prices is more pronounced, suggesting that white wines may peak in value earlier than red wines. Overall, these plots highlight that older vintages are generally priced higher, with red wines appearing to retain value for a longer period compared to white wines. This indicates that vintage year is an important factor influencing wine pricing, with older wines being more highly valued in the market.



Figure 3.2: Lowess graph of Price Against Vintage year of Red and White Wine

The total precipitation represents the total liquid and frozen water, including rain and snow, that reaches the Earth's surface. It is the combined result of large-scale precipitation, generated by the cloud scheme, and convective precipitation, generated by the convection scheme in the ECMWF Integrated Forecasting System (IFS). This parameter excludes fog, dew, or precipitation that evaporates before reaching the ground. Depending on the dataset, the accumulation period can vary: it is typically accumulated over 1 day for monthly averaged reanalysis. The unit of measurement is depth in millimeters of water equivalent, which represents the depth the water would have if uniformly spread over the area.

The three graphs (Figures 3.3, 3.4, and 3.5) illustrate the relationship between wine prices (in log form) and rainfall during the growing, maturation, and storage seasons for both red and white wines. For the growing season, moderate rainfall has a positive effect on prices for both red and white wines, though the effect is more pronounced for white wines, which show a sharper increase in price with higher precipitation. In contrast, red wine prices level off as rainfall increases beyond a certain point. During the maturation season, red wine prices initially increase with more rainfall, but excessive rain leads to a decline in prices, suggesting that too much moisture during ripening can be detrimental. White wines, on the other hand, experience a steady decrease in price as rainfall increases during the maturation period, indicating a negative impact on quality. Rainfall during the storage season has a minimal impact on both red and white wines, with only a slight downward

trend observed for red wines. Overall, these findings suggest that while rainfall is beneficial during the growing season, excessive rainfall during maturation, particularly for white wines, can reduce quality and prices. Rainfall during storage appears to have a negligible effect on wine prices.

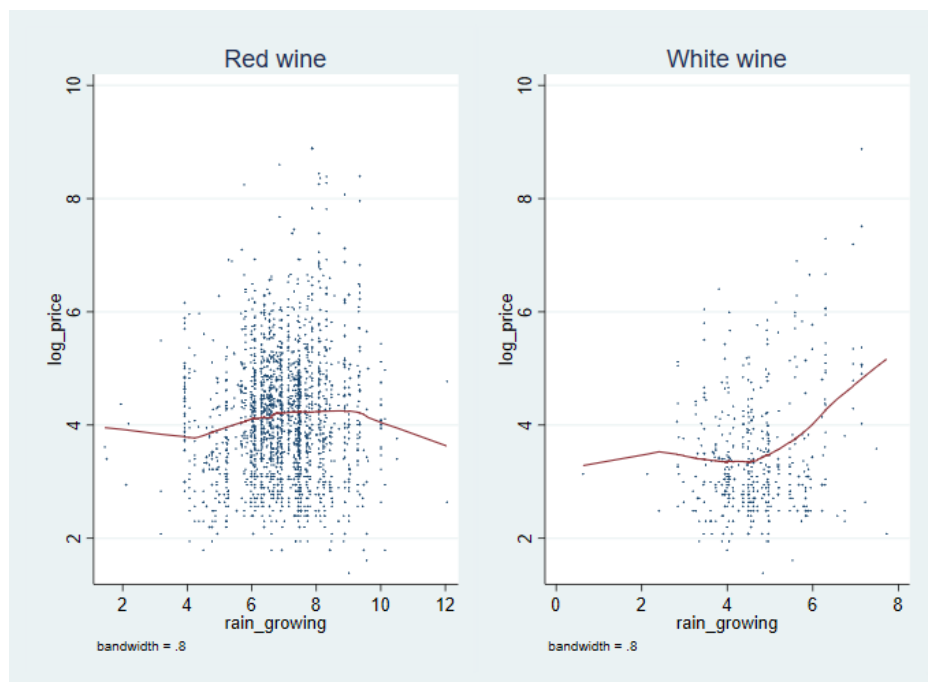


Figure 3.3: Lowess graph of Price Against rainfall in growing months of Red and White Wine

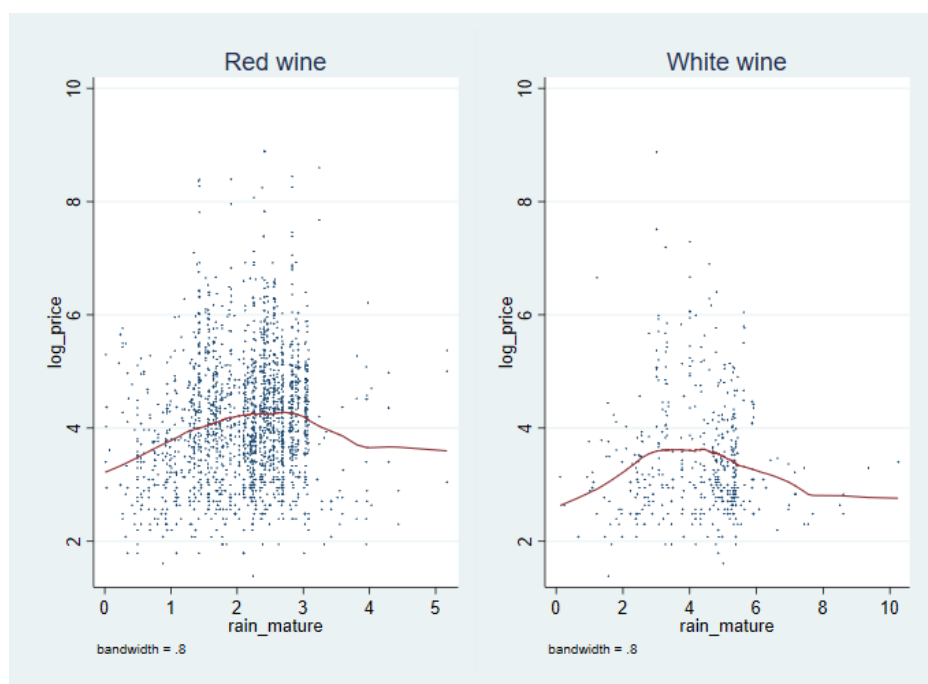


Figure 3.4: Lowess graph of Price Against rainfall in mature months of Red and White Wine

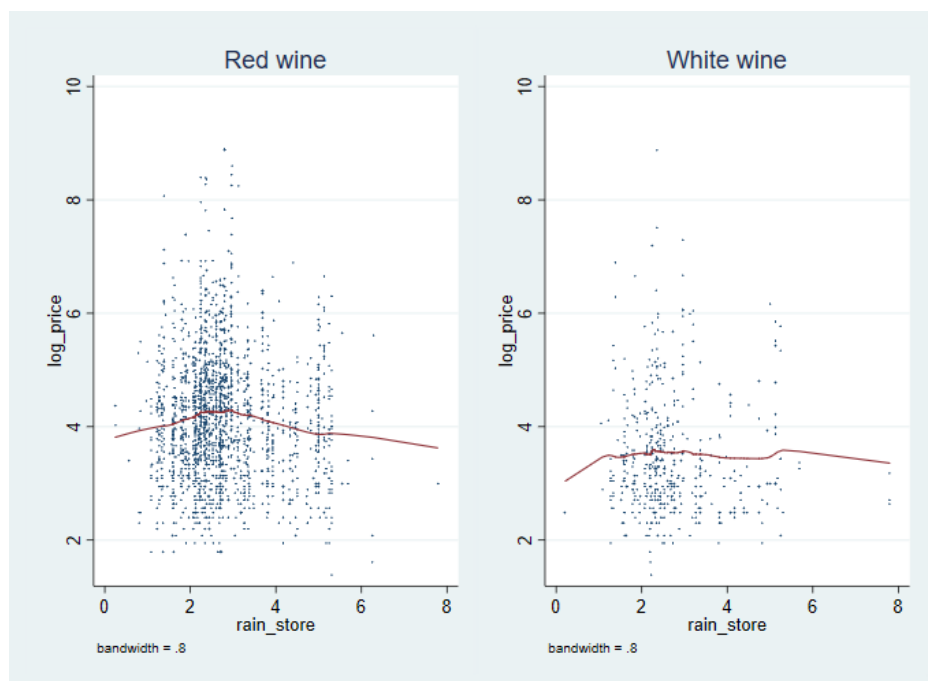


Figure 3.5: Lowess graph of Price Against rainfall in storage months of Red and White Wine

The average temperature is the mean of 2m temperature of a specific area during a month. 2m temperature refers to the air temperature measured 2 meters above the surface of land, sea, or inland waters. It is derived by interpolating between the lowest atmospheric model layer and the Earth's surface, factoring in the surrounding atmospheric conditions. This temperature is expressed in kelvin (K), but can be converted to Celsius ($^{\circ}\text{C}$) by subtracting 273.15 from the kelvin value.

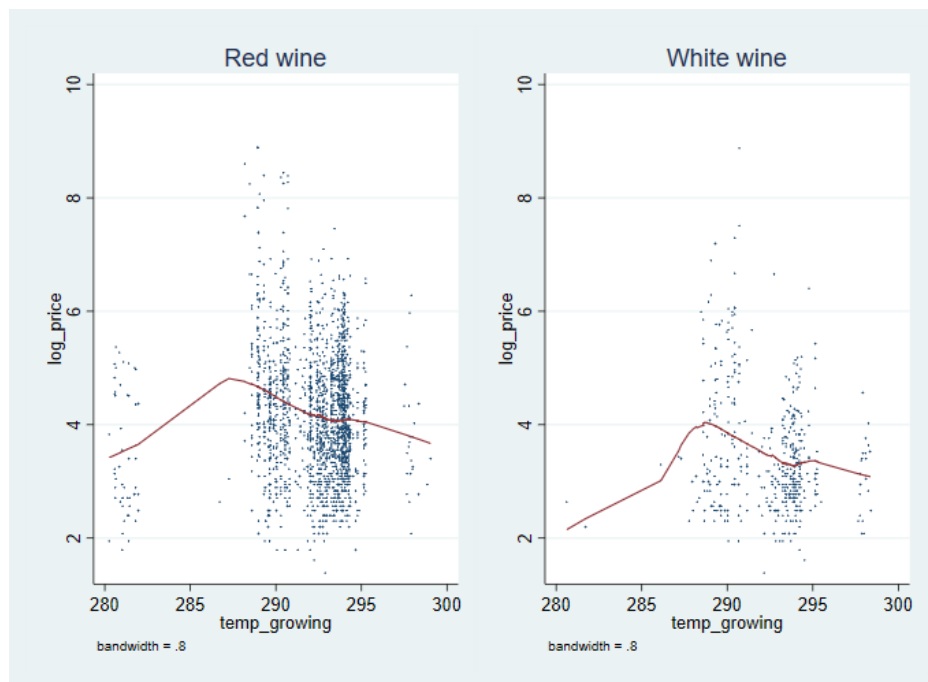


Figure 3.6: Lowess graph of Price Against average temperature in growing months of Red and White Wine

The figure 3.6 shows the LOWESS plots of wine price (in log form) against temperature during the growing season for both red and white wines. In both cases, there is an initial increase in wine prices as temperatures rise, with a peak around 580 Kelvin. After reaching this point, the prices tend to decline as temperatures continue to increase. This suggests that moderate temperatures during the growing season are favorable for grape development, leading to higher wine prices, while excessively high temperatures may negatively impact grape quality, resulting in lower prices. The similarity in patterns for both red and white wines indicates that optimal temperature ranges are crucial for maximizing the quality and market value of both wine types.

3.3.4 Descriptive Statistics

The descriptive statistics for the variables used in the regression analysis are summarized in Table 3.2. which presents key statistical measures such as the number of observations (Obs), mean (Mean), standard deviation (SD), minimum (Min), and maximum (Max) values for each variable. These statistics provide valuable insights into the distribution and variability of the data, helping to reveal underlying patterns and relationships that are crucial for the analysis.

Table 3.2: Summary Statistics

(a) Summary Statistics for Red Wine

Variable name	Obs.	Mean	SD	Min	Max
log_price	1,906	4.1693	1.1069	1.3863	8.8934
year	1,906	2001.7	9.9857	1980	2020
rain_mature	1,906	2.1217	0.7256	0.0141	5.1709
rain_store	1,906	2.7576	1.0440	0.2457	7.7932
temp_growing	1,906	284.16	1.9334	280.04	297.44

(b) Summary Statistics for White Wine

Variable names	Obs.	Mean	SD	Min	Max
log_price	454	3.5092	1.0842	1.3863	8.8754
year	454	2005.2	9.6078	1985	2020
rain_mature	454	4.2832	1.4280	0.1190	10.253
rain_store	454	2.7063	1.0611	0.2003	7.7933
temp_growing	454	284.26	3.2544	277.20	297.90

The dataset includes 1,906 observations for red wines and 454 for white wines. Red wines exhibit a higher average log price (4.17) compared to white wines (3.51), indicating a general price premium. In terms of climate conditions, both wine types share similar average growing season temperatures (around 284 K), though white wines show greater variation in budburst temperature and rainfall during the maturation stage. Overall, these summary statistics highlight observable differences across wine types, justifying separate regression analyses.

3.4 Methodology

The hedonic pricing model used in this study specifies wine price as a function of measurable product attributes and external conditions. The relationship is assumed to be linear and additive, allowing each attribute, including climate variables, vintage year, and country fixed effects, to contribute independently to price formation. The model assumes that observed prices reflect the equilibrium outcome of supply and demand under conditions of full information and competitive markets.

A particular strength of this model lies in its use of naturally occurring weather variables, such as growing season temperature and precipitation—which are plausibly

exogenous and not influenced by producer or consumer behaviour. This helps mitigate common endogeneity concerns encountered in other hedonic contexts. Importantly, the climate variables employed are drawn from Ashenfelter's (1995) foundational model of Bordeaux wine pricing, which demonstrated that a small set of weather indicators could successfully explain price variation. Building on this established structure, the present study applies the same logic to a broader dataset covering multiple countries and wine types, providing a robust framework for international generalisation.

3.4.1 Model Specification

This study employs a cross-sectional hedonic pricing framework to estimate how climate conditions during different production stages affect wine prices. Each observation corresponds to a unique wine–country–vintage combination. The dataset includes wines from multiple countries and vintage years, but does not track the same wine over time, making it cross-sectional rather than longitudinal. Climate data are matched at the country-year level. To assess robustness and control for unobserved heterogeneity, we estimate two models:

Model 1: Baseline specification (without country fixed effects)

$$\begin{aligned}\log(\text{price}_{ct}) = & \beta_0 + \beta_1 \text{year}_{ct} + \beta_2 \text{rain_mature}_{ct} + \beta_3 \text{rain_store}_{ct} \\ & + \beta_4 \text{temp_growing}_{ct} + \beta_5 \text{temp_growing}_{ct}^2 + \epsilon_{ct}\end{aligned}\tag{3.1}$$

Model 2: Extended specification (with country fixed effects)

$$\begin{aligned}\log(\text{price}_{ct}) = & \beta_0 + \beta_1 \text{year}_{ct} + \beta_2 \text{rain_mature}_{ct} + \beta_3 \text{rain_store}_{ct} \\ & + \beta_4 \text{temp_growing}_{ct} + \beta_5 \text{temp_growing}_{ct}^2 + \mu_c + \epsilon_{ct}\end{aligned}\tag{3.2}$$

In both models:

- $\log(\text{price}_{ct})$ is the natural logarithm of the average wine price in country c and vintage year t .
- vintage_year_{ct} is included as a continuous control variable to account for aging effects and secular pricing trends.
- Rainfall and temperature variables correspond to distinct production stages: growing, maturation, harvest, and storage.

- Squared terms are included to capture nonlinear effects.
- μ_c in Model 2 denotes country fixed effects, controlling for time-invariant structural differences across national wine markets (e.g., tax policy, wine culture, labeling laws).
- ϵ_{ct} is the idiosyncratic error term.

Comparing the two models allows us to assess whether the influence of climate variables remains robust after accounting for national-level unobserved heterogeneity.

3.4.2 Identification Strategy.

The identification of the climate–price relationship in this study is based on cross-sectional variation in weather conditions across countries and vintage years. Each observation represents a unique wine–country–vintage combination, and no product is observed repeatedly over time. Weather variables are matched to each country–year pair and vary due to natural climate fluctuations across geography and years.

To control for confounding influences, we include the variable `vintage_year` directly in the regression to account for secular trends in wine valuation, such as age-related price appreciation. We do not employ vintage fixed effects, since the goal is to isolate the impact of specific seasonal weather patterns rather than sweep out all year-level variation.

Country fixed effects are included and interpreted as a structural proxy for terroir—that is, the time-invariant characteristics of place such as climate, soil, wine culture, and regulatory environment. These country effects control for persistent differences in average price levels and production contexts across wine-producing regions.

Accordingly, identification of the weather effect comes from within-country, cross-vintage variation in climatic conditions, after controlling for terroir via country dummies and vintage year as a continuous regressor. This strategy allows us to estimate how short-term climatic variability during specific production stages (e.g., growing season temperature or maturation rainfall) influences wine prices across a diverse set of regions.

3.5 Results

Table 3.3: Regression Results for Red Wine; The dependent variable is $\log(\text{price})$; Model 2 includes country fixed effects.

VARIABLES	Model 1	Model 2
		(With Country FE)
year	-0.0382*** (-15.93)	-0.0392*** (-15.51)
rain_mature	0.1323*** (4.19)	0.1046* (1.95)
rain_store	-0.0538** (-2.46)	-0.0498* (-1.94)
temp_bud	-6.172*** (-6.06)	-16.904*** (-2.89)
temp_bud²	0.0160*** (5.98)	0.0296*** (2.88)
Constant	978** (6.74)	2,494*** (3.00)
Observations	1,906	1,903
Adj R-squared	0.221	0.233
Country fixed effects	No	Yes

Notes: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Temperature and precipitation variables are based on ERA5 monthly data, aggregated to relevant phenological phases: growing season, maturation, and post-harvest.

Model 2 includes country fixed effects to account for unobserved time-invariant country-level factors (e.g., regulation, land quality).

Country dummy variables are not reported in the table, as they serve solely as controls and are not of substantive interest in this study.

All models are estimated with robust standard errors.

Model 1 shows that multiple weather variables significantly influence red wine prices. Vintage year is negatively associated with price, consistent with the idea that older wines (lower vintage values) command higher prices. Rainfall during the growing season and maturation season exhibits a significant positive effect, while rainfall during the storage season is associated with a significant price reduction. Temperature during the growing season shows a strongly positive and statistically significant coefficient, but the squared term is negative, suggesting a concave relationship where moderate warmth benefits price, but extreme heat may reduce it.

However, in Model 2—after controlling for country fixed effects—the significance of many weather variables diminishes. While vintage year remains significant, rainfall during the growing and storage seasons becomes only marginally significant. The squared terms and temperature effects lose statistical significance. This suggests that much of the variation captured in Model 1 comes from cross-country differences in climate, and once country-specific unobserved heterogeneity is absorbed, the within-country variation in weather becomes less predictive of price.

Table 3.4: Regression Results for White Wine; The dependent variable is $\log(\text{price})$; Model 2 includes country fixed effects.

VARIABLES	Model 1	Model 2 (With Country FE)
Vintage year	-0.0380*** (-7.38)	-0.0347*** (-6.32)
temp_bud	-3.6786*** (-2.88)	-13.9827* (-1.76)
temp_bud²	0.00625*** (2.83)	0.02477* (1.77)
rain_mature	-0.1452*** (-3.94)	-0.1546** (-2.13)
rain_store	-0.0929** (-2.00)	-0.1085** (-2.04)
Constant	619.38*** (3.38)	2046.65* (1.82)
Observations	454	452
Adj R-squared	0.182	0.2868
Country fixed effects	No	Yes

Notes: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Temperature and precipitation variables are based on ERA5 monthly data, aggregated to relevant phenological phases: growing season, maturation, and post-harvest.

Model 2 includes country fixed effects to account for unobserved time-invariant country-level factors (e.g., regulation, land quality).

Country dummy variables are not reported in the table, as they serve solely as controls and are not of substantive interest in this study.

All models are estimated with robust standard errors.

The results for white wine show similar patterns, though with some differences. In Model 1, growing season rainfall and temperature are both statistically significant, with rainfall having a positive and temperature a negative effect on price. Rainfall

during the storage season also has a negative effect, while maturation season rainfall shows a positive impact. In Model 2, after including country fixed effects, growing season rainfall retains significance, while maturation rainfall turns negative but remains insignificant. Interestingly, the growing season temperature now becomes highly significant and negative, with a positive squared term—suggesting a U-shaped relationship, possibly indicating that both low and high temperatures reduce price, with an optimal middle range.

These patterns suggest that white wine prices may respond more consistently to climate variation across countries, even after controlling for national structural differences. The stronger R-squared in Model 2 (0.318 vs. 0.229) supports this interpretation.

3.6 Discussion

The regression results provide several important insights into the relationship between climate variables and wine prices across countries and wine types. Most notably, the analysis identifies a statistically significant U-shaped relationship between growing season temperature and price. This is evidenced by a negative coefficient for the linear temperature term and a positive coefficient for the squared term, implying that extremely low or high temperatures tend to raise wine prices. While previous agronomic studies have identified an inverted-U relationship between temperature and grape yield (Zhu et al., 2020; Sadras et al., 2012), our findings suggest the opposite pattern in terms of pricing. This contrast aligns with basic supply-side economics: moderate temperatures result in higher yields, increasing market supply and thereby putting downward pressure on prices; in contrast, extreme temperatures may reduce yields, creating scarcity and pushing prices upward. Thus, the observed U-shaped price response may be an indirect market reflection of the inverted-U yield response to temperature, validating previous agronomic findings through an economic lens.

Rainfall effects show greater heterogeneity across production stages. Precipitation during the grape maturation period exhibits a positive relationship with wine prices, possibly due to its role in promoting balanced ripening and enhancing flavor development. However, excessive rainfall during the storage period (post-harvest) tends to negatively impact wine value, likely due to its adverse effect on preservation conditions and oxidative stability. These findings underscore the importance of

considering not only climatic influences during the growing season, but also post-harvest environmental factors that affect final product quality and price.

The inclusion of country fixed effects in Model 2 alters the significance of several climate variables compared to Model 1. This difference arises because country dummies absorb time-invariant characteristics such as institutional structure, average climate, terroir reputation, and regulatory environment. As a result, Model 2 estimates rely solely on within-country, year-to-year weather variation, which tends to be narrower and statistically weaker. The observed decline in explanatory power for temperature-related variables in Model 2 should not be interpreted as evidence against their economic relevance. Rather, it highlights the trade-off inherent in fixed-effects estimation: controlling for confounding reduces omitted variable bias but also limits the available identifying variation.

Comparing red and white wines reveals both similarities and differences. In both cases, rainfall during maturation has a generally positive effect, while storage rainfall has a negative effect. However, the U-shaped relationship between temperature and price appears more pronounced for red wines, which may reflect their longer aging periods and greater sensitivity to growing conditions. Red wines also tend to exhibit stronger country fixed effects, possibly due to higher market segmentation and branding based on geographic origin.

Taken together, these findings confirm that climatic factors have economically significant impacts on wine prices, but that these effects vary by varietal, production stage, and geographic context. They also reinforce the robustness of Ashenfelter’s original insight—that simple weather variables can explain a considerable portion of price variation—while extending it to a broader, cross-national context. By highlighting the differentiated role of weather across production phases and wine types, the study offers useful guidance for vineyard management, climate adaptation, and strategic positioning in global wine markets.

3.6.1 Limitations and Future Research

This study has several limitations that point to directions for future research. First, the dataset lacks detailed information on grape variety, vineyard-level cultivation practices, and soil characteristics. These unobserved factors are crucial for identifying differences in grape quality and type, which directly influence how wines respond to

climatic variation. Their absence introduces aggregation bias and limits the ability to explore within-country or within-type heterogeneity in climate sensitivity.

While the analysis distinguishes red and white wines in regression, the same climate variables are applied across both categories without varietal-specific calibration. This pooled strategy may obscure differentiated responses, as grape varieties and wine styles can vary widely in their sensitivity to weather. Future studies could improve upon this by matching varietal-level physiological characteristics to stage-specific weather indicators, enabling better attribution of climate effects.

In addition, the analysis does not identify quality tiers or market segments within red and white wines. As argued by Costanigro et al. (2007), disregarding such heterogeneity can lead to aggregation bias in the estimated implicit prices. High-end wines or organic wines may exhibit stronger responses to climate shocks due to their production methods or quality sensitivity. Although quantile regressions in the appendix provide partial insights into price dispersion for red wines, this could not be extended to white wines due to limited sample size. Future work could incorporate expert ratings, quality certifications, or organic labeling to enable stratified analysis.

Second, the geographical scope of this study is limited to Northern Hemisphere countries. Although wines from Australia, Chile, and South Africa were initially considered, their low representation across wine types and vintages led to exclusion for statistical consistency. This restricts the generalizability of the findings, particularly regarding hemispheric differences in climate timing and phenology.

Third, all climate variables are matched at the country–year level, which may not accurately reflect localized production conditions. Weather can vary substantially across regions within the same country, especially for countries with diverse topographies and microclimates. Future research could exploit finer spatial identifiers such as sub-regional appellations or municipalities, or ideally use vineyard-level coordinates, to improve climate–price matching and isolate localized weather effects. Region-specific fixed effects or multilevel models could then be used to control for unobserved confounders without sacrificing meaningful variation.

Lastly, the current study uses a cross-sectional specification with one observation per country–vintage–wine type. Future work could expand the dataset into a panel structure, which would allow the application of dynamic estimators and better

account for temporal dependencies or lagged weather effects. Incorporating interaction terms between climate variables and production methods, quality scores, or geographic factors would further enhance explanatory power and policy relevance.

3.7 Conclusion

This study extends the classical hedonic pricing model to a broader international context, exploring how short-term climatic variability influences wine prices across major wine-producing regions in the Northern Hemisphere. Building on the foundational work of Ashenfelter et al. (1995), we move beyond the limitations of single-region analyses to evaluate the climate–price relationship across diverse national, varietal, and vintage contexts. By matching wine prices with weather data corresponding to specific production stages—including growing, maturation, and post-harvest storage—we provide new evidence on the economic sensitivity of global wine markets to climatic factors.

The results reaffirm that weather conditions remain a key determinant of wine prices, even after controlling for unobserved, time-invariant national heterogeneity via country fixed effects. In particular, growing season temperature and rainfall during the storage period consistently exhibit significant impacts on price, indicating that both quality formation during production and risks associated with post-harvest conditions are critical to market valuation. These findings not only contribute to the literature on climate-sensitive agriculture but also confirm the external validity of previous region-specific conclusions under more heterogeneous institutional and climatic conditions.

From a practical perspective, the implications of this study are multi-dimensional. For wine producers, the findings underscore the importance of temperature management during the growing season and the need to mitigate moisture-related risks during the storage phase. Adaptive strategies such as shading, temperature control, and improved drainage and ventilation systems may enhance yield stability and preserve wine quality. For investors and participants in wine markets, the demonstrated sensitivity of prices to climate variables highlights the importance of incorporating meteorological risks into asset valuation and portfolio allocation strategies. In the face of increasing climate volatility, tools such as agricultural insurance and weather derivatives may become integral to pricing frameworks. On the policy front, the results suggest that national and regional

governments should consider targeted subsidies or infrastructure investment—such as in cold-chain logistics or hillside drainage systems—to improve the resilience of local industries to climate shocks.

Several limitations remain. The absence of data on grape variety, estate identity, and regional-scale climate exposure restricts the study’s ability to account for finer-grained heterogeneity. Moreover, this analysis focuses solely on Northern Hemisphere producers, leaving unexplored the potentially asymmetric seasonal and regulatory dynamics of Southern Hemisphere wine economies.

Future research may expand this framework by incorporating grape-specific information, more localized weather data, and exploring nonlinear effects of climate shocks. Further attention could also be paid to how climate variability differently affects luxury versus mass-market wines. As global warming intensifies, understanding how climate shapes the economic geography of wine production will become increasingly vital—not only for producers and consumers but also for regional planners and climate policymakers.

3.A Appendix

3.A.1 Weather Variable Calculations

In this study, the weather variables are calculated based on the specific type of wine (red or white) and the hemisphere in which the wine is produced, ensuring that the analysis reflects the different grape-growing cycles in each region.

Rain growing is calculated as the total precipitation during critical months of the growing season. For red wines from the Northern Hemisphere, it is based on the sum of rainfall in February, April, and May, while for red wines from the Southern Hemisphere, it includes July, August, and November. For white wines from the Northern Hemisphere, rain growing is calculated using the rainfall in February and April. Last but not least, for white wines from the Southern Hemisphere, rain growing is calculated using the rainfall in April.

Rain mature, which represents rainfall during the grape maturation period, is calculated differently for each wine type. For red wines from the Northern Hemisphere, it is the total rainfall in June. For red wines from the Southern Hemisphere, it includes December and January, while for white wines from the Northern Hemisphere, it is the total rainfall in June and July.

The rain harvest variable is only used for red wines from the Southern Hemisphere and is calculated as the total rainfall in February and March, the critical harvest months.

Rain store refers to the total precipitation during the wine storage period. For red wines from the Northern Hemisphere and white wines from the Northern Hemisphere, it is based on the total rainfall in November, while for red wines from the Southern Hemisphere, it is calculated as the sum of rainfall in May, June, and July.

Temperature growing is used for white wines from both the Northern and Southern Hemispheres. For white wines in the Northern Hemisphere, it is calculated as the sum of the average temperatures in May and July, which are critical months for grape development. In the Southern Hemisphere, temperature growing is based on the average temperature in September, reflecting the key month for grape maturation in that region.

Lastly, temperature mature is only used for white wines from the Southern Hemisphere, where it is calculated based on the average temperature in February.

These tailored calculations ensure that the impact of weather conditions is accurately reflected in the analysis for different wine types and regions.

3.A.2 Descriptive Statistics for Wines from Both Hemispheres

Table 3.5: Summary Statistics

Variable	Obs	Mean	SD	Min	Max
log_price	2,648	3.9652	1.1357	1.3863	8.8934
Vintage year	2,648	2002.8	9.9070	1980	2020
rain_growing	2,648	0.0062	0.0017	0.0006	0.0121
rain_mature	2,569	0.0028	0.0014	0.0000	0.0103
rain_harvest	2,569	0.0046	0.0015	0.0001	0.0099
rain_store	2,569	0.0029	0.0014	0.0002	0.0125
temp_growing	2,648	575.90	50.669	283.49	598.09
temp_mature	79	294.33	3.7623	289.01	298.67
Wine_type	2,648	0.7987	0.4010	0	1
Hemisphere	2,648	0.8912	0.3113	0	1

3.A.3 Regression Results for Wines from Both Hemispheres

Table 3.6: Regression Results; dependent variable: price of wine in log form; models are estimated separately for red and white wines, distinguishing between wines produced in the Northern Hemisphere and Southern Hemisphere.

VARIABLES	White South log_price	White North log_price	Red South log_price	Red North log_price
Vintage year	-0.0084 (-0.69)	-0.0362*** (-7.33)	-0.0547*** (-7.14)	-0.0463*** (-20.22)
rain_growing	275.6*** (2.80)	148.0*** (2.97)	126.2* (1.94)	80.25*** (4.37)
rain_mature		-106.4*** (-3.10)	156.8** (2.30)	113.2*** (3.51)
rain_store		-156.1*** (-3.22)	-118.2** (-1.92)	-43.10* (-1.95)
rain_harvest			-102.9* (-1.99)	
temp_growing	0.0572 (0.54)	-0.0496*** (-4.48)		
temp_mature	0.0319 (0.29)			
Constant		105.4*** (9.59)	113.0*** (7.37)	96.20*** (20.98)
Observations	79	454	209	1,906
Adj R-squared	0.099	0.213	0.200	0.196

Notes: t-statistics are shown in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

Table 3.7: Regression Results for Red and White Wine

VARIABLES	White Wine (Model 1)	White Wine (Model 2)	Red Wine (Model 1)	Red Wine (Model 2)
year	-0.0366*** (-6.62)	-0.0363*** (-6.665)	-0.0446*** (0.00265)	-0.0445*** (-16.74)
rain_growing	0.0967* (1.89)	0.106** (2.072)	0.0337 (0.0211)	0.0317 (1.431)
rain_mature	-0.0322 (-0.12)	-0.105 (-1.428)	-0.0542 (0.203)	0.125** (2.273)
rain_mature²	-0.00765 (-0.28)		0.0384 (0.0446)	
rain_store	-0.0900 (-1.60)	-0.0922* (-1.658)	-0.0417 (0.0267)	-0.0506* (-1.794)
temp_growing	-23.39** (-2.49)	-24.37** (-2.519)	-13.12*** (4.711)	-13.51*** (-2.850)
temp_growing²	0.0404** (2.50)	0.0420** (2.532)	0.0226*** (0.00807)	0.0232*** (2.858)
Australia (4)	2.915** (2.43)	2.748** (2.534)		
Chile (6)	-0.364 (-0.20)		-1.450 (0.972)	
France (7)	3.617*** (3.89)	3.626*** (3.860)	1.590*** (0.484)	3.100*** (3.226)
Germany (8)	2.976*** (2.98)	2.946*** (2.968)	0.779 (1.097)	2.297* (1.727)
Greece (9)	1.600** (2.00)	1.552** (2.103)	-0.299 (1.030)	
Hungary (10)	2.577** (2.16)	2.617** (2.178)		
Israel (11)	0.482 (0.45)		0.213 (0.524)	
Italy (12)	2.144*** (2.69)	2.169*** (2.694)	1.200*** (0.424)	2.741*** (2.654)
Lebanon (13)			1.055 (1.041)	
Portugal (14)	1.975* (1.71)		1.094** (0.476)	
Spain (16)	2.233** (2.55)	2.213*** (2.593)	0.693 (0.430)	2.288** (2.211)
USA (17)	2.201*** (3.19)	2.257*** (3.196)	1.082*** (0.382)	2.601** (2.520)
Uruguay (18)			0.425 (0.872)	
Constant	3.462** (2.52)	3.607** (2.555)	1,998*** (687.4)	2,055*** (2.973)
Observations	454	449	1,906	1,837
R-squared	0.321	0.318	0.239	0.238

3.A.4 quantile Regression Results for Red Wine

Table 3.8: Quantile Regression Results

VARIABLES	25th Quantile	50th Quantile	75th Quantile
vintage	-0.0385*** (0.003)	-0.0380*** (0.003)	-0.0478*** (0.004)
rain_growing	0.0491* (0.026)	0.0688*** (0.025)	0.0809** (0.035)
rain_mature	0.2153*** (0.047)	0.2359*** (0.044)	0.2293*** (0.063)
rain_store	-0.0584* (0.030)	-0.0878*** (0.029)	-0.1148*** (0.040)
temp_growing	6.7925*** (1.534)	8.9091*** (1.464)	6.1419*** (2.076)
temp_growing ²	-0.0117*** (0.003)	-0.0154*** (0.003)	-0.0106*** (0.004)
Constant	-907.2383*** (223.744)	-1212.8310*** (213.566)	-785.9098*** (302.727)
Observations	1,837	1,837	1,837
R-squared	0.1143	0.1171	0.1109

Note: Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The dependent variable is logarithmic price.

Table 3.9: Regression Results for Red Wine (With quality variable); The dependent variable is $\log(\text{price})$; Model 2 includes country fixed effects.

VARIABLES	Model 1	Model 2
		(With Country FE)
year	-0.0410*** (-8.93)	-0.0477*** (-8.86)
rain_mature	0.4241*** (5.25)	0.2470*** (2.73)
rain_store	-0.1270*** (-3.79)	-0.0441 (-1.13)
temp_bud	-10.927 (-0.97)	-14.201 (-1.26)
temp_bud²	0.0191 (0.97)	0.0249 (1.25)
Quality_dummy	0.2965*** (3.39)	0.2958*** (3.19)
Constant	1,644.23 (1.03)	2,125.77 (1.33)
Observations	586	586
Adj R-squared	0.286	0.305
Country fixed effects	No	Yes

Notes: t-statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To further identify vintage years associated with unusually high wine quality, we construct a binary indicator (**quality_year_dummy**) that flags high-quality vintages based on wine critic scores (**pro_score**). Specifically, for each combination of country and wine type (Red/White), we regress **pro_score** on year dummies using ordinary least squares (OLS). We retain only those year coefficients that are statistically significant at the 10% level. Among these, we compute the average coefficient, and assign a dummy value of 1 to years with a coefficient greater than or equal to this average, and 0 otherwise. This approach allows us to flexibly detect vintages that exhibit relatively superior perceived quality within their respective group. The resulting dummy variable is merged back into the dataset and exported for further analysis. A plot comparing the average **pro_score** across years—grouped by the dummy variable—confirms that vintages flagged as high-quality indeed tend to receive higher critic scores.

However, this procedure results in a notable reduction in sample size, as many

group-level regressions either fail to produce statistically significant year effects or do not satisfy basic estimation conditions (e.g., too few observations, limited year variation, or zero score variance). In particular, for white wine observations, none of the country–wine type combinations yielded significant year dummy coefficients at the 10% level. Consequently, `quality_year_dummy` is systematically missing for white wine and only partially observed for red wine, which must be considered when interpreting results based on this variable.

Chapter 4

Is Wine a Veblen Good?

4.1 Introduction

In 1899, the American economist Thorstein Veblen introduced the theory of “conspicuous consumption” in his book *The Theory of the Leisure Class* (Veblen, 1899). According to this theory, the demand for certain types of good increase in response to increases in their own prices, due to their appeal as status symbols. Goods with this property have come to be known as “Veblen Goods”. The Veblen phenomenon is clearly very interesting to economists because it amounts to a violation of the almost universal “Law of Demand”.

In this chapter, we set out to test the Veblen hypothesis in the context of wine consumption. For the present purposes, we define the Veblen effect as the situation in which a particular wine becomes more desirable to consumers as the price increases, even after controlling for true quality. The idea here is that consumers are using price as a signal of quality in an irrational way, by unquestioningly assuming that a higher-priced wine is of higher quality. Another interpretation is that consumers are drawn to higher prices, regardless of actual quality, simply in a quest to signal “economic power”.

Wine lends itself well to the Veblen phenomenon because it has an unusually high level of heterogeneity of consumer preferences (Amerine and Roessler, 1976; Lecocq and Visser, 2006; Festa et al., 2016; Di Vita et al., 2019). There are an enormous variety of wines, originating from grapes of different types, grown in different regions, and harvested at different times. Even for wines produced using grapes of the same variety, region, and vintage, significant differences can arise due to variations in grape quality and the distinct practices employed by different wine producers. All of these factors contribute to the diversity and uniqueness of wines, making each product distinct in its own way. This level of diversity is one important reason why many researchers believe that consumers without professional knowledge, perhaps burdened by choice overload and confused by technical jargon, may resort to price as a signal for quality, and make (possibly irrational) purchase choices on this basis (Mastrobuoni et al., 2014).

Our test of the Veblen effect is performed in the context of a weighted regression model with average customer rating as the dependent variable, and the log of price as an independent variable. The key to the empirical strategy is that the “true quality” of the wine is controlled for, by including “expert rating” as an independent variable in the regression. If the log of price has a positive effect on customer rating,

even controlling for true quality in this way, we may conclude that there is evidence of a Veblen effect. We also allow for possible endogeneity of price using climate variables in the year of production as instruments.

Similar goals have been pursued using experimental data, notably by Goldstein et al. (2008) and Almenberg and Dreber (2011). While these studies enjoy the advantages of experimental control, our use of field data brings the considerable advantage of a large sample size, and consequently higher statistical power. To our knowledge, this paper is the first attempt to test the Veblen effect wine using field data from the wine market.¹

This Chapter is organised as follows. Section 4.2 briefly surveys the relevant literature. Section 4.3 describes the data sources and data collection procedure, and also provides summary statistics and some exploratory data analysis. Section 4.4 describes the empirical strategy. Section 4.5 presents results of estimation of the model described in Section 4.4. Section 4.6 provides further results from models estimated allowing for endogeneity of price. Section 4.7 concludes.

4.2 Literature

4.2.1 Previous studies

There is an extensive literature on the Economics of wine prices. Recent excellent surveys are provided by Le Fur et al. (2024) and Núñez et al. (2024). In much of this literature, the focus is on the determinants of wine prices. Typically, the hedonic pricing model is used to identify the determinants of price, of which there are many. Some studies focus on the effect of climate in the year of production (Ashenfelter et al., 1995; Ashenfelter, 2008), some on the effects of vintage year and maturity (Jones and Storchmann, 2001; Dimson et al., 2015), some on the effects of *terroir*² (Gergaud and Ginsburgh, 2008; Cross et al., 2011*b,a*), some on the effect of reputation (Landon and Smith, 1998), and finally some on the effects of expert ratings (Oczkowski, 1994; Schamel and Anderson, 2003).

This paper is concerned not with the determinants of price, but rather with the reverse problem: the effect of price on customer satisfaction. Many studies have

¹although see Sun (2025) which contains a preliminary version of this work.

²“Terroir” is a French term used in viticulture, to describe the unique characteristics of the environment in which the wine is produced, including soil, topography, and methods of production.

found a positive relationship between price and customer ratings (Schiessl, 2024) or between price and expert ratings (Oczkowski, 1994; Hilger et al., 2011). However, in a certain sense these results are not surprising, because the finding that customers or experts assign higher ratings to higher-priced wines is surely in part because higher-priced wines tend to be of higher quality, and hence price is simply acting as a proxy for quality.

The research gap that this paper aims to address is the investigation of the effect of price on customer satisfaction, *while controlling for true quality*. To be completely clear, the question we set out to answer is: if a consumer is faced with the choice between two different wines of exactly the same objective quality, but differing prices, do they prefer the one with the higher price? From an economic-theoretic perspective, such a preference is clearly irrational, violating the almost universal “law of demand”. However, one behavioural explanation for the anomaly is found in the theory of “conspicuous consumption” (Veblen, 1899), according to which consumers of luxury goods are prepared to spend more in situations in which their spending is a public display of economic power. For this reason, we will refer to the anomaly as the “Veblen effect”. One intriguing manifestation of the Veblen effect is the phenomenon of restaurant customers tending to choose the second-cheapest wine on the wine list as an embarrassment-avoidance strategy. This theory has been tested by De Meza and Pathania (2021) using price data collected from restaurant wine lists, although they find no evidence in favour of a Veblen effect and conclude the “second-cheapest” rule is an urban myth.

There is some experimental evidence consistent with the Veblen effect. Experimental control is clearly valuable in this setting, since it enables the experimenter to administer “blind tastings”, that is, wine-tasting treatments in which prices are not known by participants. Goldstein et al. (2008) and Ashton (2014) both find that when non-expert wine-consumers have no information on price, the unknown price has no effect on their enjoyment. Almenberg and Dreber (2011) find that telling subjects that a wine is high-priced leads to higher satisfaction ratings, albeit with mild significance and only for female participants. In another controlled laboratory experiment, Plassmann et al. (2008) found that higher (deceptive)³ prices were consistently associated with higher pleasantness ratings, while lower (deceptive) prices were linked to lower pleasantness ratings. These

³“Deception” in this context means that participants were deliberately given false information about the prices of the wines being tasted. Nearly all experimental economists argue strongly against the use of any sort of deception in experiments, mainly because of the clear sense in which it “pollutes the pool of experimental subjects” (Bardsley et al., 2010).

findings were further supported by observing increased activity in the medial orbitofrontal cortex when participants perceived higher prices. Similar results from an fMRI study were obtained by Schmidt et al. (2017).

To our knowledge, Sun (2025) is the only researcher to have tested the Veblen effect, in the sense defined above, using field data from the wine market. As mentioned in Section 4.1, the use of field data sacrifices the advantage of experimental control, but gains the considerable advantage of a much larger sample size, and consequently higher statistical power. The empirical strategy required in order to identify the Veblen effect, and the one adopted in this paper, is to estimate the effect of price on consumer satisfaction while controlling for true quality. True quality will be measured by expert ratings. There is much evidence of the validity of expert ratings as a measure of true quality, for example, Hilger et al. (2011); Landon and Smith (1997); Lecocq and Visser (2006); Ali et al. (2008); Cardebat et al. (2014).

Field data has been used to test for the Veblen effect in other markets. For example, Abrate et al. (2021) analyse a large data set of hotel-guest review ratings, and find that price has a negative effect on ratings, which is consistent with the law of demand, not the Veblen effect.⁴ This result is perhaps unsurprising in the context of hotel rooms, because it can be expected that hotel customers have a firm idea of what they expect for a given price, and are therefore likely to react negatively if the price is “too high”. A similar result is found by Cao et al. (2003) in the context of the online book market. These results provide support for what is known as “expectancy-disconfirmation theory” (Anderson and Sullivan, 1993).

Clearly endogeneity is likely to cause problems in models of the wine market, as a consequence of simultaneity in the determination of quantity, quality and price. This problem has been addressed in hedonic pricing models. Kaimann et al. (2023) and Dubois and Nauges (2010) both use expert ratings in previous periods as instruments to deal with the possible endogeneity of expert ratings. Oczkowski (2019) uses weather variables in the year of production, vintage, and producer fixed effects as instruments for quality. In this paper, we face a similar problem, with the difference that we are seeking instruments to account for the possible endogeneity of price in a model of customer satisfaction.

⁴Abrate et al. (2021) refer to the Veblen effect as the “placebo effect”.

4.3 Data

4.3.1 Data Sources

This study utilizes a curated selection of popular wines featured on the *Wine Spectator* platform⁵. *Wine Spectator* is a leading wine publication renowned for highlighting wines of strong market visibility and critical acclaim. A wine is uniquely identified by a name and a vintage year. The data was collected in October 2023. After removal of duplicates, the final sample comprises 1,698 red wines and 368 white wines, with vintage years ranging from 1980 to 2020. To complete the dataset, we matched each wine to data contained in *Wine-Searcher*,⁶ including retail price, number of customer reviews, average customer rating, and average expert score.

Table 4.1 presents descriptions of the variables used in the analysis, and the symbols used for each.

Table 4.1: Variable Definitions

Variable	Symbol	Description
Price	p_i	Average sale price of wine i (£/750ml)
Customer rating	y_i	Average customer rating of wine i (from 1 to 5 stars)
Number of reviews	n_i	Number of customer reviews for wine i
Expert rating	z_i	Average expert rating for wine i (from 0 to 100)
Vintage year	v_i	Year of production (minus 2000) of wine i

The variable “price” is the average wine price provided by *Wine-Searcher*, which was computed by the following process. Firstly, all prices available for a particular wine were standardized to a 750ml equivalent. Subsequently, the average prices were obtained, excluding the highest and lowest 20 percent of prices in order to avoid distortions caused by pricing errors. In instances where a limited number of prices are available, the median was employed as a more reliable measure. This approach ensures the accuracy and reliability of the average price data provided by the website.

Also extracted from *Wine-Searcher* is the variable “customer rating”. Following purchase of the wine, customers are invited to provide feedback, including the

⁵<https://www.wine-searcher.com/winespectator-top100>

⁶*Wine-Searcher* is one of the most influential online platforms for wine information and pricing, including expert ratings from renowned experts such as Robert Parker and Jancis Robinson. URL: <https://www.wine-searcher.com/marketplace>

assignment of a rating between 1 star and 5 stars. Average ratings for each wine, rounded to the nearest 0.5, are reported on the website.

4.3.2 Exploratory Data Analysis

Tables 4.2a and 4.2b provide summary statistics for the key variables, for red wine and white wine respectively.

Table 4.2: Summary Statistics

(a) Summary Statistics for Red Wine

Variable name	Obs.	Mean	SD	Min	Max
Price (£/750ml)	1,698	145.9	409.0	4.0	7,284
average customer rating	1,698	4.0	0.5	1	5
Number of reviews	1,698	6.7	8.8	1	108
Expert rating	1,698	90.9	2.3	73	99
Vintage Year (minus 2000)	1,698	2.0	9.3	-20	19

(b) Summary Statistics for White Wine

Variable names	Obs.	Mean	SD	Min	Max
Price (£/750ml)	368	65.4	145.0	4.0	1,828
average customer rating	368	3.9	0.5	2	5
Number of reviews	368	3.3	2.4	1	21
Expert rating	368	90.4	2.1	84	97
Vintage Year (minus 2000)	368	5.0	8.4	-14	20

Figure 4.1 presents two histograms. The first shows the distribution of wine price. It is clear that most prices are between £0 and £200, and that there is a very long tail to the right. Note from Table 4.2a that the highest price in the data set is £7,284. The second histogram shows the distribution of $\log(\text{price})$ and this is much closer to symmetry. For this reason $\log(\text{price})$ will be used as the price variable in the model estimated in the next section.



Figure 4.1: Price distribution

Figure 4.2 presents two lowess plots showing the effect of vintage year on customer rating, for red wine (left plot) and white wine (right plot). It is clear in both cases that the effect of vintage year on customer rating is U-shaped. We may infer that, as the wine starts to age, customer ratings fall, but when the wine gets beyond a certain age, ratings rise. For both red and white wine, the “nadir” vintage appears to be soon after 2000.

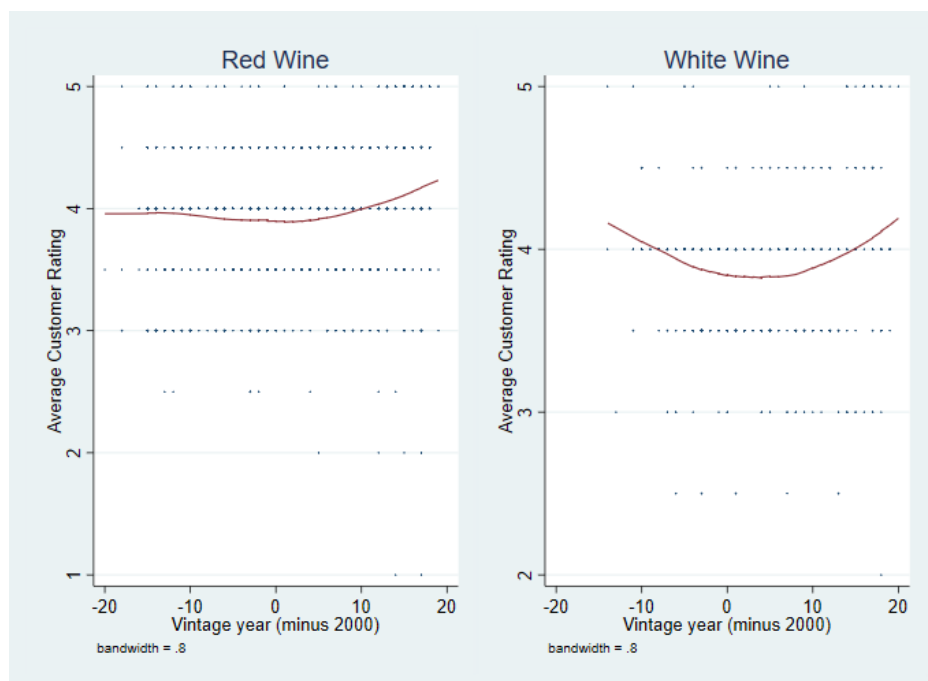


Figure 4.2: Lowess graph of Average Customer Rating (minus 2000) against Vintage year of Red and White Wine

Certain other plots are very useful in uncovering the relationships between key variables. Figure 4.3 shows that vintage year has a pronounced negative effect on price for both red and white wines, indicating unambiguously that older vintages command higher prices. Figure 4.4 shows that expert rating (representing true quality) has a strong positive effect on customer ratings. This is likely to be partly because customers are in genuine agreement with experts in their assessment of quality, and partly because customers are influenced by expert ratings when passing judgement.

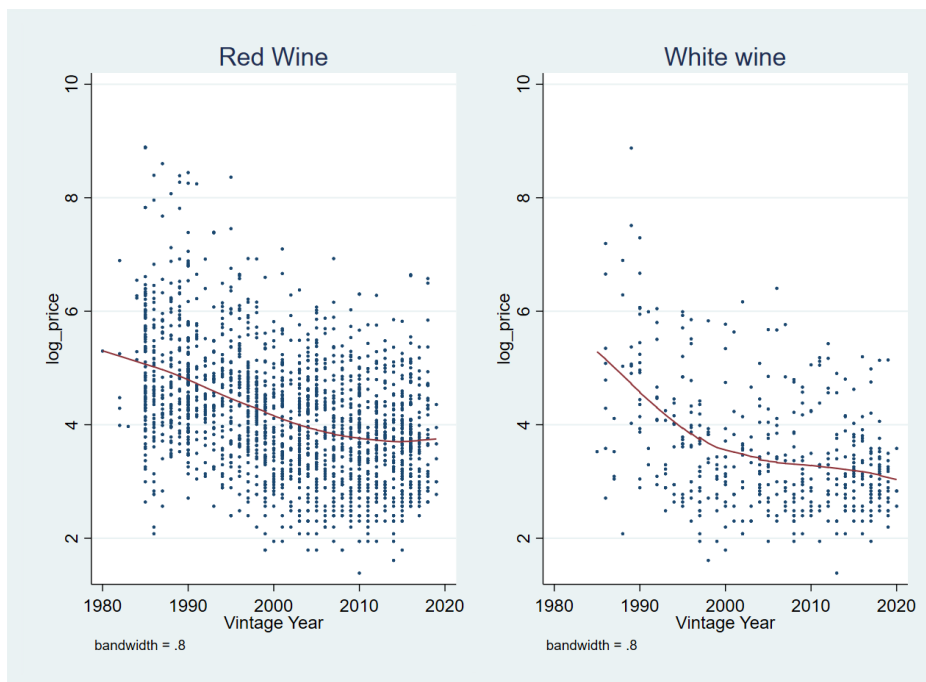


Figure 4.3: Lowess graphs of $\log(\text{price})$ against vintage for red wine and white wine

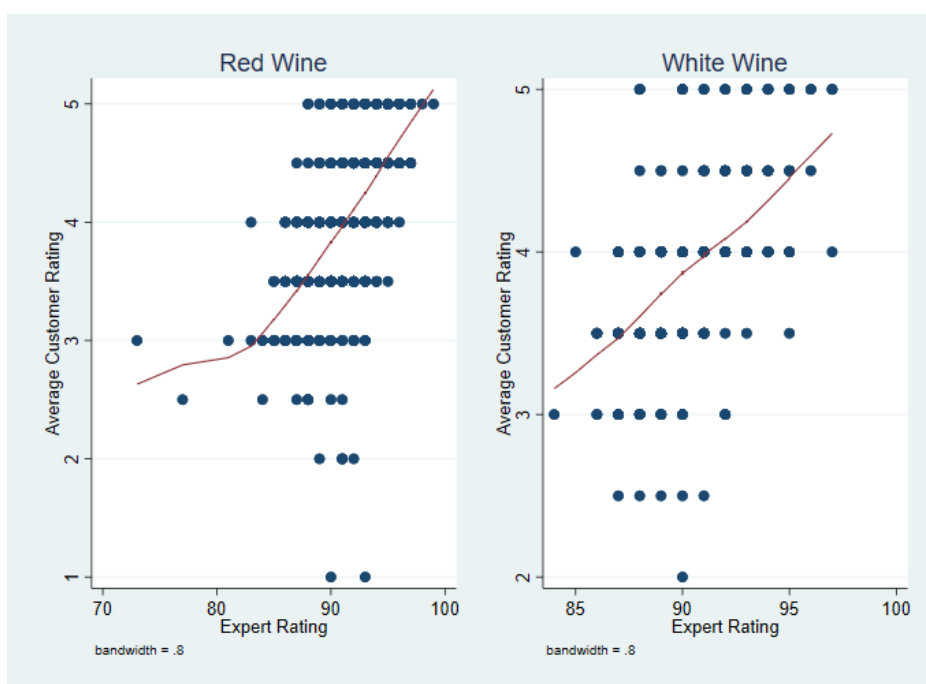


Figure 4.4: Lowess graph of average customer ratings against expert rating.

4.4 Empirical Strategy

As mentioned above, a particular wine is identified by name and vintage. Let there be N different wines in the sample, and let us index each individual wine with i .

Variables were defined in Table 4.1 above. y_i is the average customer rating for wine i , where this average is taken over n_i customers. p_i is the (average) price of wine i . z_i is the average expert rating for wine i . v_i is the vintage year, defined as the year in which the wine was produced, minus 2000.

We will estimate the following model:

$$y_i = \alpha + \beta \ln(p_i) + \gamma z_i + \delta_1 v_i + \delta_2 v_i^2 + u_i \quad i = 1 \dots N \quad (4.1)$$

The “expert rating”, z_i , will be interpreted as a measure of the “true quality” of the wine. Naturally we expect the parameter γ to be positive since we expect customers to attach higher ratings to wines of higher true quality. The most important feature of (4.1) is that, by including z_i , we are controlling true quality, so that the parameter β associated with $\ln(p_i)$ may be interpreted as a pure price effect. In particular, $\beta < 0$ would be consistent with the “Law of Demand”, while $\beta > 0$ would imply a Veblen effect. We further control for the effect of vintage year, reflecting factors such as market ageing effect ⁷. For this, we apply a quadratic specification by including v_i^2 in addition to v_i , in the light of the clear u-shaped curves seen in Figure 4.2 above.

It is important that the dependent variable, y_i , is the *average* customer rating over a number n_i of customers. This means that estimation of (4.1) requires weighted regression, with weights depending positively on n_i .

4.5 Results from Weighted OLS Regression

Table 4.3 presents the results from two weighted regression models, estimated separately for red wine and white wine.⁸ The first model (“without”) is estimated without controlling for true quality (expert rating). The second model (“with”) controls for true quality by including expert rating. As expected, without controlling for true quality, both red and white wines exhibit a significant positive effect of (log)

⁷Older vintages are generally rarer and tend to command higher prices due to their limited availability and potential appreciation over time. However, vintage year may also correlate with quality, as certain years experience more favourable climatic conditions. Importantly, these climate-related quality effects are not uniform across regions and can only be properly captured through interactions with geographic variables. This heterogeneity and its implications were explored in greater detail in Chapter 3, where vintage effects were analysed alongside weather data at the country level.

⁸Similar analyses were carried out for dessert wines and sparkling wines. Results are reported in Table 4.5 of the Appendix.

price on customer rating, because price is simply acting as a proxy for quality.

Table 4.3: Weighted Regression results; dependent variable: average customer rating; weights depend positively on number of customer ratings used to compute average; models estimated separately for red and white wines; Models estimated without and with controlling for true quality.

	Red (Without)	Red (With)	White (Without)	White (With)
Price (log)	0.293*** (36.42)	0.100*** (8.68)	0.216*** (10.51)	0.041 (1.56)
Expert rating		0.111*** (23.25)		0.122*** (9.39)
Vintage year	0.017*** (15.21)	0.003** (2.31)	0.008* (1.84)	0.003 (0.81)
Vintage year ²	0.001*** (6.27)	0.001*** (6.81)	0.001** (2.08)	0.001** (2.26)
Constant	2.663*** (68.31)	-6.584*** (-16.50)	2.992*** (35.38)	-7.358*** (-6.65)
Observations	1,698	1,698	368	368
R-Squared	0.469	0.599	0.250	0.389

Notes: t-statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

It is only through the inclusion of the expert-rating variable that we can effectively test for the presence of the Veblen effect. When this variable is included, the coefficient of (log) price remains strongly positive for red wine, but becomes insignificant for white wine. These results lead to an intriguing inference: red wine appears to fit the Veblen good category, while white wine does not, although for white wine, the law of demand does not appear to hold either.

4.6 Allowing for Endogeneity of Price

A key endogeneity concern in this model is reverse causality: customer ratings may influence consumer demand and, in turn, affect wine prices. For example, higher satisfaction scores can act as electronic word-of-mouth (eWOM), boosting demand and pushing prices upward. This creates a two-way relationship between price and satisfaction that biases OLS estimates. To address this, we estimate model (4.1) using an instrumental variables (IV) strategy that isolates exogenous variation in price unrelated to product quality. We use weather conditions from the growing season prior to bottling as instruments. These variables are widely recognized in the wine economics literature for their influence on supply and pricing (Ashenfelter and Storchmann, 2016), but they are unlikely to directly affect quality of wine. This

exclusion is essential for identifying the Veblen effect, which requires that price variation not reflect quality differences.

4.6.1 Weather Variables as Instruments

A valid instrumental variable (IV) in this study should influence wine prices through supply-side variation, such as yield shocks, while remaining exogenous to unobservable wine quality characteristics. In this context, growing season temperature serves as a strong candidate: it directly affects grapevine yields through physiological development and water balance, but has limited or no direct effect on sensory wine quality, especially when post-harvest vinification and branding processes are controlled for.

Grapevines (*Vitis vinifera*) follow a well-defined annual phenological cycle, beginning with bud break in March or April in the Northern Hemisphere, followed by bloom, berry growth, maturation, and ultimately dormancy in late autumn. These developmental stages are primarily determined by growing season temperatures⁹ (Amerine and Winkler, 1944; Winkler, 1974; Jones et al., 2012). Therefore, early-season temperatures, particularly average temperatures in March and April, play a critical role in triggering bud break and shaping subsequent phenological development. Based on this relationship, we use average temperature during March–April as an instrument for growing season conditions, reflecting its exogenous and biologically grounded influence on vine development.

It is well known that weather variables pertaining to the time of production are highly important in explaining the price of a vintage wine (Ashenfelter, 2010), and hence these variables satisfy one of the key requirements for instruments. An ideal instrumental variable (IV) in the present situation is one that affects wine prices via supply-side channels, such as yield shocks, without directly influencing unobservable quality.

A growing body of empirical research highlights that grape yield is significantly influenced by weather variability during the early phenological stages, including flowering and fruit set (Ashenfelter and Storchmann, 2016; Puga et al., 2023; Dominguez et al., n.d.; Blanco-Ward et al., 2019; van Genuchten, 2023). These studies consistently report that temperature increases during bud-break stages

⁹The regression results in Table 4.6 show that temperature does not have a statistically significant effect on professional scores.

(March and April) advance phenology, alter fruit set success, and ultimately affect total yield outcomes. Notably, evidence from panel data and climate modeling indicates that the yield response to weather conditions—particularly temperature and precipitation—often follows an inverse U-shaped relationship: moderate warming or rainfall can enhance yield, while extremes in either direction (e.g., heatwaves or excessive rainfall) suppress it (Puga et al., 2023; Blanco-Ward et al., 2019).

Although precipitation affects grapevine water balance, its impact on yield depends on additional factors such as soil water-holding capacity and irrigation practices (Gambetta, 2016; Jones et al., 2012; Schultz, 2016). In many regions, water supply is actively managed. We have found that using early-season (March and April) precipitation as an instrument is unsatisfactory due to insignificance and over-identification failure, whereas early-season (March and April) mean temperature has a highly significant effect in the price equation. We therefore instrument with a quadratic regression in temperature to flexibly approximate its nonlinear effect on grape yield. This choice reflects both theoretical relevance and empirical precedent: temperature influences grape yields and thus wine prices, but is unlikely to directly affect final wine quality or taste.

4.6.2 Empirical Strategy

To address potential endogeneity of price, we also estimate a two-stage least squares (2SLS) model in which $\ln(p_i)$ is instrumented using weather conditions during the early growing season. Specifically, we use the average temperature in March and April (denoted T_i), as this variable has been shown to significantly influence grapevine development and yield, but is unlikely to affect the final sensory quality of wine. We therefore specify the first-stage equation as follows:

$$\ln(p_i) = \pi_0 + \pi_1 T_i + \pi_2 T_i^2 + \pi_3 z_i + \pi_4 v_i + e_i \quad (4.2)$$

The inclusion of T_i^2 allows for a flexible, nonlinear effect of temperature on price, reflecting the agronomic literature suggesting an inverse U-shaped yield response to temperature. By substituting the fitted values $\ln(\hat{p}_i)$ from (4.2) into the main equation (4.1), we estimate the effect of exogenous price variation—driven by climate shocks—on customer satisfaction. This IV strategy relies on the assumption that growing season temperature influences prices through supply-side channels (yield) only, and is uncorrelated with unobserved quality determinants beyond expert ratings, as discussed in Section 4.2 and Chapter 3.

4.6.3 Results from Weighted IV Regression

Table 4.4 presents data from the weighted IV regression, again performed separately for red and white wine. In the first stage regression, (log) price is regressed on expert rating, vintage year,¹⁰ and rain in the growing season. Fitted values of (log) price from this regression are then used as the price variable in the second stage regression.

Table 4.4: Weighted IV Regression Results; dependent variable of first stage regression: log(price); dependent variable of second stage regression: average customer ratings; log(price) variable used in the second stage is the prediction from the first stage; models estimated separately for red and white wines.

	Red Wine		White Wine	
	first stage	second stage	first stage	second stage
pred. (log) Price		0.033*** (2.91)		-0.193** (-3.10)
Expert rating	0.329*** (49.16)	0.136*** (28.12)	0.355*** (19.64)	0.205*** (8.23)
Vintage year	-0.062*** (-31.36)		-0.033*** (-6.38)	
temp(growing season)	-3.66*** (-4.50)		-0.05*** (-4.49)	
temp(growing season) ²	0.01*** (4.43)			
Constant	506.22*** (4.34)	-8.49*** (-21.02)	-12.80*** (-3.39)	-13.96*** (-6.81)
Underidentification test	853.746 (0.000)		68.045 (0.000)	
Weak Instrument test	570.746 (22.30)		41.287 (19.93)	
Overidentification test	2.121 (0.346)		0.847 (0.358)	
Observations	1,698	1,698	368	368
R-squared	0.711	0.580	0.566	0.226

Notes: t-statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01. For the Underidentification and Overidentification tests, p-values appear in parentheses. For the Weak Instrument test, the number in parentheses is the critical value.

From the second-stage results, we see that (log) price still has a strongly positive effect on customer rating for red wine, implying that we have evidence of the Veblen effect for red wine even after allowing for endogeneity of price. In contrast, we see that (log) price now has a strongly negative effect on customer rating for white wine, implying that white wine satisfies the law of demand.

¹⁰There is no need to include the square of vintage year in the first stage regression, because, as clearly seen in Figure 4.3, the effect of vintage year on price is monotonic.

4.6.4 Instrument Validity Tests

Three tests of Instrument Validity have been performed, and the results are reported in Table 4.4 above.

First, the under-identification test tests the null hypothesis that the equation is under-identified. The strongly significant test statistics seen for both red and white wine indicate that the model is identified and the instruments are valid in both cases. Second, the weak identification test tests the null hypothesis of zero correlation between the instruments and the endogenous variable (Stock and Yogo, 2002). Table 4.4 reports the test statistic, and alongside it, the critical values prescribed by Stock and Yogo (2005). In both cases, we see test statistics that greatly exceed the respective critical values, implying that the instruments are not weak. Finally, the over-identification test tests the null hypothesis that the instruments are exogenous and uncorrelated with the error term (Hayashi, 2011). For both red and white wines, the test produces non-significant p-values. This indicates that the instruments are exogenous in the second-stage regression, adding further confidence to the reliability of the results.

Together, these tests validate the results reported in Table 4.4 by supporting the reliability of the instruments used. This is the case for both red and white wines.

4.7 Limitations

While weather variables provide a useful source of exogenous variation for identifying price effects, other important supply-side factors may also influence wine prices but are not accounted for in our model. These include vineyard management practices, technological inputs, labour costs, and vineyard size. Due to data unavailability, we are unable to control for these dimensions in the current analysis. Future research may address this limitation by incorporating more detailed production-side data to better isolate the drivers of wine pricing.

4.8 Conclusion

The Veblen effect is usually taken to refer to the phenomenon of the demand for a good increasing as the price increases, contrary to the law of demand. In this paper,

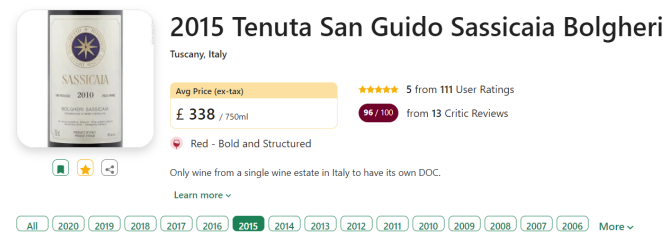
we have not considered the effect of price on demand, but instead the effect of price on ex-post customer satisfaction, the latter being measured using customer ratings. When this effect is positive, we claim to have found evidence of a Veblen effect. We are interpreting the effect in terms of an entirely irrational response in which a high price is being used unquestioningly to infer high quality. Of course, there may be other explanations at play here. A positive effect of price on reported satisfaction might be a manifestation of “choice-supportive bias” or “post-purchase rationalization (Lind et al., 2017). However, regardless of the source of the anomaly, it can be claimed that a positive effect of price on customer ratings is consistent with the Veblen effect even in its traditional sense, because there is much evidence of the positive effect of customer ratings on demand (Hyrynsalmi et al., 2015).

The reason why consumers might display this sort of irrationality for wine but not for other types of goods (e.g. books, hotel rooms) is likely to be because the nature of wine is such that the average consumer has imperfect knowledge about the quality of wine, not only at the time of purchasing it, but also at the time of consuming it. Moreover, the nature of the market makes knowledge hard to acquire, since consumers may feel burdened by choice overload (Beneke, 2015) and lost in a sea of labels and tasting notes. For these reasons it would not be surprising if consumers turn to the straightforward and easily-accessible metric of price as the deciding factor in their own assessment of the quality of the wine.

Experimental research has previously been conducted which has found evidence for the Veblen effect for wine, in the sense defined here (Almenberg and Dreber, 2011). The present paper is, to our knowledge, the first study that pursues similar goals using field data. We find results that are consistent with previous experimental findings. Customers are influenced by price, in the sense that they report higher satisfaction for wines of higher price, even when true quality is controlled for. Interestingly, we have found strong evidence of the Veblen effect for red wines, but no such effect for white wines.

One considerable advantage of using field data over experimental data for this purpose is the larger sample size, which leads to higher statistical power. This is the likely reason for the strongly significant positive price effect that we have obtained, in contrast to the mildly significant effects seen in previous experimental studies.

4.A Appendix



2015 Tenuta San Guido Sassicaia Bolgheri
Tuscany, Italy

Avg Price (ex-tax)
£ 338 / 750ml

★★★★★ 5 from 111 User Ratings
96 / 100 from 13 Critic Reviews

Red - Bold and Structured

Only wine from a single wine estate in Italy to have its own DOC.

Learn more ▾

All 2020 2019 2018 2017 2016 2015 2014 2013 2012 2011 2010 2009 2008 2007 2006 More ▾

Figure 4.5: Data scraping page

TOP 100 LISTS

About the List

We've revealed the Top 10 Wines of 2022!

Each year, *Wine Spectator* editors survey the wines reviewed over the previous 12 months and select our Top 100, based on quality, value, availability and excitement. This annual list honors successful wineries, regions and vintages around the world.

Here you'll find every Top 100 list from 2022 back to the debut year, 1988. Since then, new regions, grapes and styles have appeared on the list, but the classics are still going strong. Enjoy browsing more than 30 years of the world's top wines!

For detailed profiles of all of the 2022 picks, check out the complete Top 100 Wines of 2022 package in the Dec. 31, 2022, issue of *Wine Spectator*, available on newsstands starting Nov. 29, or [buy a back issue](#) when they become available.

(Note: In 1998, some wines share the same rank, as the list was divided into top reds, whites and dessert wines.)



Figure 4.6: top 100 wine of Wine Spectator

Score	Explanation
95–100	Classic: a great wine
90–94	Outstanding: a wine of superior character and style
85–89	Very good: a wine with special qualities
80–84	Good: a solid, well-made wine
75–79	Mediocre: a drinkable wine that may have minor flaws
50–74	Not recommended

Wine Spectator 100-Point Scale

Figure 4.7: Wine searcher 100-point scale

Table 4.5: Regression results using vintage year as panel variable

	Wine type			
	Red	White	Dessert	Sparkling
pro_score	0.111*** (0.005)	0.122*** (0.012)	0.121*** (0.025)	0.172*** (0.044)
log_price	0.074*** (0.012)	0.028 (0.027)	0.160* (0.092)	0.111 (0.147)
Constant	-6.431*** (0.434)	-7.244*** (1.063)	-7.714*** (2.041)	-12.334*** (3.915)
Observations	1,892	437	92	36
R-squared	0.392	0.317	0.541	0.591
Number of vintage_panel	41	34	31	20

Standard errors in parentheses
 * p<0.1, ** p<0.05, *** p<0.01

Table 4.6: Effect of Growing Season Temperature on the Quality of Red and White Wines

	Red Wine	White Wine
<i>temp_growing</i>	1.936 (2.129)	1.931 (4.848)
<i>temp_growing</i> ²	-0.00328 (0.00368)	-0.00324 (0.00830)
<i>Constant</i>	-194.64 (308.15)	-197.45 (707.61)
Observations	1,899	580
R-squared	0.0021	0.0028

Standard errors in parentheses
 None of the coefficients are statistically significant

Chapter 5

Conclusion

The purpose of this chapter is to briefly summarise the thesis, to draw attention to possible limitations of the work carried out, and to suggest possible directions for further research.

Chapter 2 reported on a meta analysis which analysed a data set drawn from many previous studies testing the effect of eWOM. The style of meta analysis chosen was to use p-values as the dependent variable. This choice makes possible a comparison between different types of study. While meta analysis using p-values has been used by other authors, to our knowledge this is the first study to take account of situations in which the information provided in the study is such that the exact p-value is unknown, but instead an interval of possible p-values can be inferred from the available information. This called for the use of the random-effects interval regression model. Using this model, we obtained some interesting and meaningful results, and we recommend the use of this approach to other practitioners conducting meta-analyses.

Chapter 3 reported on a hedonic pricing model in which the prices of wines were explained using a set of variables representing weather conditions around the time of production of the wine. It must be conceded that this model is an unusual form of hedonic pricing model, since the independent variables are not physical attributes of the product. However, we are following the pioneering work of Ashenfelter et al. (1995), Ashenfelter (2008, 2010) who emphasised the importance of the weather variables. We included regional-dummies in the model, and we claimed that these captured differences in “terroir” between different regions. Clearly we would like to extend the model to include other variables such as soil type, farming practices and geomorphological factors, and these considerations provide a clear direction for further research.

A point that was stressed in Chapter 3 was that the main purpose of the hedonic pricing model was to identify the weather variables that would qualify as valid instruments for the price variable in the model of Chapter 4. We appear to have met this objective, since the selected weather variables passed all of the tests to which we subjected them to Chapter 4, when investigating their performance as instruments.

In Chapter 4, we reversed the direction of causality, by investigating the impact of wine price on customer reviews. The main result we obtained here is that, for red wine at least, price has a positive effect on customer satisfaction, even after controlling for the true quality of the wine. This is quite a striking result because it implies that red wine is a “Veblen good”, and essentially violates the almost-universal “law of demand”. It implies that consumers are being irrationally influenced by the price of the product, in that they assume that a higher price necessarily implies a better product. The reason why consumers display this sort of irrationality for wine but not for other types of good (e.g. hotel rooms) is likely to be because the nature of wine is such that the average consumer is not fully informed about the quality of wine, even while consuming it.

As a final point, we note that the result we have obtained regarding the irrational response to higher wine prices has previously been obtained by Almenberg and Dreber (2011) using experimental data. As previously mentioned, we are the first to obtain this result using field data. It is interesting to compare the statistical significance of the results between the two studies. Almenberg and Dreber (2011) obtained a p-value of 0.088 based on a sample size of 135. We obtained a p-value less than 0.01 based on a sample of 1698. It is evident that our results are more statistically significant than those of Almenberg and Dreber (2011), which at first sight appears to contradict our finding in Chapter Two, that experimental studies lead to more significant test results than observational studies. However, given that our sample size is considerably larger than theirs, this difference in significance is unsurprising.

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