The impact of hail on retail wine sales: Evidence from Switzerland

Alexandre Mondoux

Changins – Haute école de viticulture et œnologie, HES-SO // Haute école spécialisée de Suisse occidentale, Nyon, Switzerland
Email: alexandre.mondoux@changins.ch

Abstract

This paper uses a difference-in-differences approach to analyze the treatment effect of a hail weather shock in a specific Swiss wine-growing region. We exploit a natural experiment from Switzerland's Three Lakes wine region in 2013 and examine its impact on the country's retail market. We find statistically significant (1%-level) effects of –22.8% and +2.8% for the volume and price of wine consumed, respectively. These effects can be interpreted as average treatment effects, which is the difference in outcomes between treatment and control groups using a pre-post shock study methodology. Several robustness checks confirm the statistical significance of the estimated effects and the initial assumptions.

Keywords: difference-in-differences; retail sector; weather shock; wine economics

JEL Classifications: C14; C21; C33

I. Introduction

The present article studies how hail damage to a grape harvest affected wine sales in the retail sector in Switzerland. We exploit a natural experiment that occurred in a specific Swiss wine region. On June 20, 2013, a violent hail storm hit the canton of Neuchâtel (in our data, Neuchâtel forms part of the Three Lakes region along with the Lake Bienne and Vully regions), causing significant damage and very important losses for the entire vineyard sector (République et Canton de Neuchâtel, 2013). The Three Lakes region's 2013 harvest was 43.7% lower than in 2012 (FOAG, 2014), and the storm also affected the Geneva region and the Jura mountain areas of the canton of Vaud.

Switzerland's vineyard area covers about 15,000 hectares, 0.2% of the world total according to OIV (2019), and is divided into six wine regions. The country borders the significant wine-producing countries of France and Italy. With an average production of 90 million liters per year, Switzerland's domestic production covers only 37.7% of its total wine consumption (FOAG, 2014). This has led to a very competitive market with a high share of foreign wines. The main grape varietals are Pinot Noir,

Chasselas, Gamay, Merlot, and Müller-Thurgau.[1] Swiss wine exports are very low, representing only about 1.1% of its production, including the re-exportation of wines that transit through Switzerland (FOAG, 2019).

Switzerland's 2013 grape harvest varied considerably from one region to another. For example, Ticino, one of our methodology's five control wine regions, experienced an abundant grape harvest, in contrast to the region hardest hit by the hailstorm—the canton of Neuchâtel—whose wine production fell by 54% compared to 2012 (FOAG, 2014). The wine harvests in the adjacent Lake Bienne and Vully regions also fell, by 34.2% and 17.5%, respectively.

To estimate this weather shock's effects, we chose a difference-in-differences (DID) approach for a specific treatment group (the Three Lakes region) and a pre-post study design. The cut-off date, which defines the pre-post shock analysis limit, was set at April 2014, the approximate date when the first 2013 vintages arrived in Swiss supermarkets.[2] We subsequently fixed March 2015 as the last period in our analysis, because the 2014 vintage should not have been affected by 2013's hail storm effect. Anticipation effects on the retail market in the period just after the weather shock information and before April 2014 will be analyzed in terms of supply assortment and pricing. This type of weather supply shock should be exogenous, as hailstorms appear suddenly and are very difficult to forecast in advance. Measures to limit weather damage in the wine-growing sector, such as hail nets, are quite expensive.

The panel scanner dataset used in this article enabled us to identify consumer purchasing patterns and interpret them as an equilibrium between the demand and supply of wine. The dataset includes all the types of wines sold (quantity) and prices per liter in Switzerland's major supermarket chains, as scanned at the till (Nielsen, 2015).[3] To position our analysis in 2013, 29.4% of the wine sold on the retail market was Swiss wine (Nielsen, 2015), whereas the consumption of Swiss wine represents 39.2% of total wine consumption (FOAG, 2014).

This paper's main motivation was to contribute to understanding wine consumers' behavior in the face of a weather shock, using Switzerland's retail market reaction and exploiting a unique and completely exogenous hailstorm in a specific wine region at a specific time. Estimating this weather shock's impact on consumer behavior should help Switzerland's cantonal and federal agricultural departments, professional wine associations, and wine producers take appropriate economic policy decisions, as will be discussed in the conclusion.

This paper proceeds as follows: Section II describes a review of the literature on the DID method and the impact of weather shocks on consumer behavior. Section III presents the dataset and provides descriptive statistics on the quantities and prices of Swiss wines in the retail market. Section IV describes our identification strategy and econometric methodology. Section V presents and analyzes the results, and Section VI focuses on several robustness checks. Section VII reveals the study's conclusions.

---

[1]For more information, see Swiss Wine Promotion SA's website at https://swisswine.ch/en/vineyard/key-figures.

[2]Our wine data does not have vintage date information, so we have assumed that harvests in year t enter the retail market as wine in April of year $t + 1$.

[3]Included Coop, Denner, Manor, Globus and Volg, and Spar supermarket chains, but not Landi, Lidl, Aldi, or Otto's (Delaquis et al., 2015a).

II. Literature review

This section focuses on the literature describing the impact of weather shocks on consumer behavior, the DID methodology, and describe the contribution to the wine economics field.

Weather's impact on consumer behavior has been studied quite extensively in the economic literature. For example, Murray et al. (2010) conducted three mixed-methods studies on the weather's effects on consumer spending using psychological mechanisms in the laboratory and in the field. Their analysis of five different products found that consumers' willingness to pay increased as exposure to sunlight rose, through a reduction in negative effects. Similarly, Tian, Cao, and Song (2021) studied weather's impact on consumer behavior and retail performance by examining 1.62 million consumers at 146 stores in China. The main climatic variables used were sunshine, rain, air quality index, and daily store sales, which were analyzed as an indicator of retail performance. Tian, Cao, and Song (2021) showed that consumers tended to buy more products at a higher price in rainy weather, whereas they bought fewer and cheaper products when temperatures were higher. Results varied depending on the product category characteristics.

Ginsburgh, Monzak, and Monzak (2013) analyzed the effects of production technologies and weather conditions on the red wines of 102 châteaux in the Médoc region (1980–1989). They demonstrated that technology and weather conditions explained up to 85% of price variations after controlling for the French wine classification of 1855. Turvey, Weersink, and Chiang (2006) developed a new pricing model for weather insurance for when harvests are affected by weather shocks and their timing. They used data on ice wine in Southern Ontario's Niagara Peninsula (Canada). Given that this study could be extended to other agricultural contexts, our analysis could have similar policy implications for insurance when estimating losses in the quantity and value of the wine produced after a specific hail shock at a specific time. Haddad et al. (2020) used a Computable General Equilibrium (CGE) model for Chile to estimate the effects of short-term climatic conditions on vineyard earnings. They found a significant reduction in Chilean real GDP of about 0.067%.

Regarding our methodology, since the seminal works of Ashenfelter (1978), Card and Krueger (1994), and Ashenfelter and Card (1985), the use of DID methodology has become widespread in empirical economics (Imbens and Wooldridge, 2009; Angrist and Pischke, 2008). Ashenfelter, Ciccarella, and Shatz (2007) analyzed foreign policy's effects on commerce using the United States' 2003 boycott of French products (more specifically, French wines), following the French government's refusal to support the war in Iraq. In contrast to the impressions given by French businessmen, Ashenfelter, Ciccarella, and Shatz (2007) used a sales dataset of nearly 4,700 individual wine brands to show that there was no boycott effect. The concurrent lower sales of French wine were mainly due to a cyclical peak during the winter holidays and a general secular decline in the consumption of this type of product in the United States. Karlsson, Nilsson, and Pichler (2014) analyzed the 1918 influenza pandemic's impact on Sweden's economic performance using DID econometric methodology. They exploited seemingly exogenous variations of effects across Sweden's regions to

estimate the pandemic's impact on earnings, capital returns, and poverty. Porcelli and Trezzi (2019) proposed an innovative identification strategy to measure the impact of earthquakes, which are considered idiosyncratic shocks on economic activity for the regions affected. They used a ranking measure for the severity of the damage, starting from the epicenter and therefore enabling a gradual diminishing treatment effect from the center outwards.

All the above authors focused more on demand determinants and demand shocks. Their methodologies and variables were pertinent in a certain way to the present study as we focused on the retail market. Given that our study focused on a specific negative supply shock, we assumed that demand would stay constant. The combination of a DID methodology, other specific methods, and variables related to the retail market for wine makes this a new and unique analysis.

III. Data

The panel wine data, which was constructed from the Swiss retail market till scanner data (Nielsen, 2015), contains monthly sales, quantity, and price data (more precisely, it is 4-weekly data consisting of 13 observations) from 2012. In the cross-sectional dimension (at the individual level), we tracked 78 different types of AOC[4] wines (see Table 1[5]) identified by the dummy variable AOC_i, the Swiss region of origin, the grape varietal, and the color of the wine.

According to Swiss Wine Promotion S.A., Switzerland has six different wine regions. They are identified in the variable $region_i$, which labels the Valais, Vaud, Geneva, Ticino, Three Lakes, and German-speaking wine regions of Switzerland. It is important to note that the first four wine regions are also individual cantons. The particularity of the Three Lakes region—the paper's treatment group—is that it includes the canton of Neuchâtel, the Lake Bienne region (in the canton of Bern), and the Vully region (on Lake Morat and is split between the cantons of Fribourg and Vaud). The German-speaking part of Switzerland, analyzed as a region in itself, can be divided using the $canton_i$ variable into Zurich, Graubünden, Schaffhausen, and "other cantons." It is important to mention that, by tradition, the Vaud wine region identifies its wines by their sub-regions, whereas in the Valais wine region, grape varietal types matter more (e.g., Chasselas, Pinot noir, or Syrah). Therefore, the $sub-region_i$ variable only concerns the Vaud wine region (La Côte, Lavaux, Chablais, Bonvillars–Côtes de l'Orbe, and a general Vaud appellation). Using this panel data structure, we could also identify the $color_i$ of the wine (red, white, or rosé).

This study only considered AOC wines (78 types), as non-AOC wines could not identify the Three Lakes treatment region because their appellations cross cantonal borders. Foreign wines are affected by so many economic and social factors outside our control that it was difficult to include them within the framework of this article. Table 2 presents descriptive statistics for the treatment and control groups for the entire sample of Swiss AOC wines from 2012 to 2015. The three main variables of

---

[4]*Appellation d'origine contrôlée* ("controlled designation of origin" in English).

[5]The names of the types of wines in the treatment group (Three Lakes) and the control group (the regions of Valais, Vaud, Geneva, Ticino, and the German-speaking part of Switzerland) are not reported here but are available from the author upon request.

Table 1 Number of individuals AOCs by group

Individuals AOCs (types of wines)	Red	White	Rosé	Total
Treatment group (Three Lakes)	**4**	**8**	**3**	**15**
Neuchâtel	2	6	1	9
Lake Bienne	1	1	1	3
Vully	1	1	1	3
Control group	**23**	**24**	**16**	**63**
Valais	6	6	2	14
Vaud	5	5	5	15
Geneva	6	6	3	15
German CH	4	4	4	12
Ticino	2	3	2	7
Total	**27**	**32**	**19**	**78**

interest for each type of wine (individual AOCs) were income (in CHF 1,000), quantity (in 1,000 liters), and mean price (in CHF/L). The price-promotion data (income-promo, quantity-promo, and price-promo) are also included in the panel. According to Nielsen (2015), these represent the types of wines that experienced reductions in their prices of at least 20% for a maximum of 4 weeks and then returned to their previous prices. These six variables were also transformed into a natural logarithm as per the requirements of econometric estimations.

Table 2 also shows different types of control variables (covariates), divided between economic variables, such as exchange rates (FTA, 2015), the Swiss Consumer Price Index (FSO, 2015), wine import prices (Swiss-Impex, 2015), and climatic variables such as temperature, wind, sunshine, rainfall, and air pressure (MeteoSwiss, 2016). To construct our climatic variables, we chose one weather station from each of the six wine regions: Sion (Valais), Lausanne (Vaud), Geneva City (Geneva), Locarno (Ticino), and Zurich (German-speaking part of Switzerland). As per Murray et al. (2010) and Tian, Cao, and Song (2021), these economic and climatic variables were included in the model as controls (see also Dobis et al. (2019) and Lessoua, Mutascu, and Turcu (2020)). Note that the economic variables were individual-invariant as they did not vary across the treatment and control groups. The 15 labels in the treatment group represent about 20% of the total number of AOC wines (78), but only about 10% of the quantity mean with respect to the control group.

The proportional volumes of wines sold on the Swiss retail market could be different from the proportional volumes of the overall wine sector, which includes other distribution channels such as direct sales, HoReCa (hotels, restaurants, and cafés), and wholesalers. For example, Valais is over-represented in Switzerland's retail market, whereas Geneva and the Three Lakes are under-represented. The Valais region, Switzerland's largest wine region, has bigger wine producers whose brands can reach the quotas necessary for acceptance by supermarkets. The proportions of the three wine colors (red, white, and rosé) also differ according to region.

Table 2 Descriptive statistics by treatment and control group

Variable	Treatment group			Control group		
	Mean	Before	After	Mean	Before	After
Dependent variable						
Income (CHF)	44.771	48.301	41.099	356.521	371.584	339.014
Quantity (L)	2.986	3.346	2.611	30.262	31.882	28.378
Price (CHF/L)	19.725	19.521	19.937	15.388	15.298	15.494
Income promo (CHF)	12.417	12.238	12.563	148.682	154.572	142.675
Quantity promo (L)	0.939	0.995	0.892	14.047	14.818	13.260
Price promo (CHF/L)	15.790	15.175	16.276	13.672	13.533	13.812
Economic variable						
Exchange rate EUR/CHF	1.180	1.219	1.131	1.180	1.219	1.131
Exchange rate GBP/CHF	1.478	1.469	1.490	1.478	1.469	1.490
Exchange rate USD/CHF	0.936	0.928	0.945	0.936	0.928	0.945
Consumer price index (CPI)	101.549	101.867	101.147	101.549	101.867	101.147
Import price Italy red (CHF)	8.152	8.204	8.087	8.152	8.204	8.087
Import price Italy white (CHF)	4.881	5.016	4.711	4.881	5.016	4.711
Import price France red (CHF)	14.569	16.601	12.008	14.569	16.601	12.008
Import price France white (CHF)	9.848	10.108	9.521	9.848	10.108	9.521
Import price Spain red (CHF)	6.784	6.747	6.830	6.784	6.747	6.830
Import price Spain white (CHF)	4.903	5.113	4.637	4.903	5.113	4.637

(*Continued*)

Table 2 (*Continued.*)

Variable	Treatment group			Control group		
	Mean	Before	After	Mean	Before	After
Climatic variable						
Temperature mean (°C)	10.764	9.673	12.139	11.129	10.068	12.467
Temperature minimum (°C)	1.599	−0.021	3.641	1.755	0.624	3.181
Temperature maximum (°C)	21.519	20.821	22.399	22.838	22.095	23.774
Wind mean (km/h)	11.934	11.876	12.008	9.678	9.721	9.623
Wind maximum (km/h)	78.704	79.059	78.257	63.988	64.773	62.998
Sunshine (hours)	153.296	145.976	162.525	165.738	160.593	172.226
Rainfall (mm)	77.872	85.082	68.781	86.167	90.711	80.437
Air pressure minimum (hPa)	1000.868	1000.630	1001.168	1000.526	999.994	1001.196
Air pressure maximum (hPa)	1029.842	1029.304	1030.519	1029.838	1029.233	1030.602
Observations	780	435	345	3,276	1,827	1,449
No. of labels	15	15	15	63	63	63
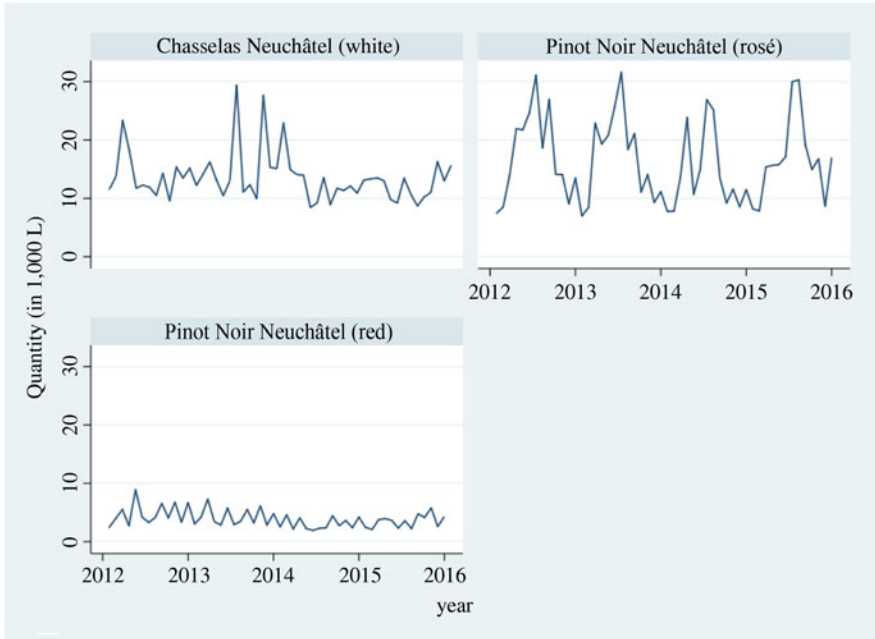
Figure 1. Seasonality of three treatment region's wines' sales.
Source: Author's illustration using data from Nielsen (2019).

Figure 1 shows the seasonality of supermarket sales of three different types of wines, one for each color, from the Neuchâtel area of the Three Lakes region. We observe that Pinot noir Neuchâtel (rosé) enjoys peak sales in the summer, as one might expect for rosé wines in general[6] given that they are consumed more during the summer's higher temperatures and greater sunlight. The Chasselas Neuchâtel (white) seems to be consumed in larger quantities during the winter (except for price-promotion effects) as it is traditionally paired with Switzerland's cold weather, and cheese-based dishes like fondue and raclette. Meanwhile, Pinot Noir Neuchâtel (red) exhibits random sales behavior across the months and years. This evidence about the seasonality of the quantities of wine sold is addressed in the following analyses because it demonstrates the usefulness of considering time fixed effects (FE) in our regression estimations. It also shows that the seasonality of wine sales, depending on the color, is somehow related to climatic variables (Murray et al., 2010; Tian, Cao, and Song, 2021).

IV. Identification strategy: Difference-in-differences

A. Identifying assumptions and definitions

Following developments by Lechner (2011) and Karlsson, Nilsson, and Pichler (2014), we can analyze and test several identifying assumptions of the DID model.

---

[6]Delaquis et al. (2015b) have dedicated a special chapter to correlations between rosé wine consumption and temperature.

(1) Stable unit treatment value assumption (SUTVA)

The SUTVA assumption states that only one potential outcome is observable for each individual, the treatment individuals being studied are all represented, and there are no relevant interactions between the individuals (Rubin, 1977). The exogenous supply shock does not interact with the wine harvest in the Three Lakes and other regions. In addition, it should not have any relevant spillover effects on the sales of wine from the treatment group compared to the control group. As there could be a compensation effect from the Swiss retail market sector, we therefore estimated the hail weather shock's net effect, that is, the direct effects minus the compensation effect (described in the Results section).

(2) Common trend

This assumption states that differences in time trends between the wine regions result only from differences in their weather shock exposure. "The dynamics of the outcomes would have been similar if the exposure to treatment had also been similar" (Karlsson, Nilsson, and Pichler, 2014). Nevertheless, if the outputs—the quantities of wine sold by the treatment and control groups—were very different, this would not be a problem. The common trend assumption is discussed in the Results section.

(3) No effect prior to treatment

This assumption rules out the possibility of a behavioral change in the treatment group that could influence their pre-treatment outcome by anticipating future treatment (Lechner, 2011). The hail weather shock was completely exogenous and could not be anticipated as it came suddenly and gave wine producers practically no possibility to protect their vineyards. Swiss supermarkets could have anticipated the effects of the hail by removing Three Lakes wines (prior to vintage 2013) from their shelves before the introduction of the affected 2013 vintage. This anticipated effect will be discussed in the Results section.

(4) Exogeneity

The exogeneity assumption concerns the covariates that are used in different results specifications, and they should not be influenced by the treatment effect so as not to destroy the identification strategy. The weather shock should not influence the main economic and climatic covariates in any significant way because the Three Lakes is a small wine region without much market power, which is set at the microeconomic level as opposed to the macroeconomic level (Lechner, 2011). The general equilibrium model could therefore be considered constant given this hail weather shock. Econometric specifications, with covariates, are provided in the regression results.

(5) Mean independence

This assumption states that exposure to treatment should be uncorrelated with the effects of treatment. The hail shock was completely random in the sense that it could have affected any of the Swiss wine regions, supporting this assumption (Karlsson, Nilsson, and Pichler, 2014).

(6) Definition of the average treatment effect (ATE)

Starting with Equation (1), we define the expected outcome for the treatment region versus the control group and for the pre-shock versus post-shock as follows:

$$E\{Y_i^{T=t} | D_i = d\} = \beta_0 + \beta_1\, d + \beta_2 t + \beta_3(dt) \tag{1}$$

$$d = \begin{cases} 0 \text{ if control group} \\ 1 \text{ if treatment group (Three Lakes)} \end{cases}$$

$$t = \begin{cases} 0 \text{ if pre-treatment period } (01/2012 - 03/2014) \\ 1 \text{ if treatment period } (04/2014 - 03/2015) \end{cases},$$

with $Y_i^{T=t}$ Outcome (such as quantity, price, and income) and $\beta_0, \beta_1, \beta_2, \beta_3$ = parameters. Each coefficient can be interpreted as follows:

- $\beta_0 = E\{Y_i^{T=0} | D_i = 0\}$

  This is the expected outcome of the control group in the pre-treatment period.

- $\beta_1 = E\{Y_i^{T=0} | D_i = 1\} - \beta_0 = E\{Y_i^{T=0} | D_i = 1\} - E\{Y_i^{T=0} | D_i = 0\}$

  This is the difference in the outcome between the treatment and the control group in the pre-treatment period.

- $\beta_2 = E\{Y_i^{T=1} | D_i = 0\} - \beta_0 = E\{Y_i^{T=1} | D_i = 0\} - E\{Y_i^{T=0} | D_i = 0\}$

  This is the difference in the outcome for the control group in the treatment period compared to the pre-treatment period.

- $\beta_3 = E\{Y_i^{T=1} | D_i = 1\} - \beta_0 - \beta_1 - \beta_2 =$
  $[E\{Y_i^{T=1} | D_i = 1\} - E\{Y_i^{T=0} | D_i = 1\}] - [E\{Y_i^{T=1} | D_i = 0\}$
  $-E\{Y_i^{T=0} | D_i = 0\}]$

  This is the difference in the outcome between the treatment group in the treatment period versus the pre-treatment period minus the difference in the outcome between the control group in the treatment period versus the pre-treatment period (Average Treatment Effect = ATE). Therefore, β_3 is the coefficient of interest, which we will focus on for the results section of this paper.

B. Exogenous supply shock

According to economic theory, given constant demand, a negative supply shock will have a positive impact on price and a negative impact on quantity. Hail weather shocks, which are, by definition, exogenous, cannot be predicted in advance by a model, and accordingly, their impact can only be estimated ex-post. Our paper focuses on the effects of the exogenous supply-side shock, the hailstorm, which impacted the Three Lakes wine region. We would expect the resulting impact to be an automatic fall in the quantities of wine sold from the treatment region on the market and a price rise. This weather phenomenon could lead to a compensation effect, that is, a rise in demand for Swiss wines unaffected by the hailstorm, an increase in their quantities on the market, and a rise in their prices. We analyze this compensation effect in the Results section through the cross-price elasticity estimations for the wines of the Three Lakes and the other five Swiss wine regions, by color.

One important issue in this setup is the Three Lakes region's wine stocks, which could be used to compensate for the losses in wine production (due to the low harvest) and to maintain a constant supply and deliveries to the retail market. According to Switzerland's Federal Office for Agriculture, the Three Lakes region's stocks fell by 31.6% for white wines and 29.7% for red and rosé wines in 2013 (FOAG, 2016). These data are, however, limited as we did not have precise information for other distribution channels (HoReCa, wholesale, direct sales) to study their diversification effects. Our data (Nielsen, 2015) represent about one-third of the total volume of Swiss wines available in the country's market. With a lower wine supply available for the market due to the hail weather shock, we would expect producers to sell a greater share to their private consumers (direct sales) and perhaps restaurants (HoReCa) given the higher margins. On the other hand, only big wine producers have enough wine (usually 50–100,000 liters) to sell through retail market channels, and they usually have long-term contracts with distributors, which are difficult to terminate. Local consumers in the affected wine region could go directly to the grower, but, in general, the greater the physical distance, the less likely it is. A sensitivity analysis of these diversification effects is presented in the Results section.

C. Econometric model (baseline)

To identify whether sales of the treatment group (Three Lakes) wines significantly dropped in Switzerland's retail market after the weather shock, we use the following DID equation:

$$\ln(Outcome_{i,t}) = \beta_0 + \beta_1 Treat_i + \beta_2 Post_t + \beta_3(Treat_i * Post_t) + \varepsilon_{i,t} \qquad (2)$$

Equation (2) is a random effect (RE) model, where we regress the $Outcome_{i,t}$ (quantity, price, income) on the dummies $Treat_i$, $Post_t$, and $(Treat_i * Post_t)$, where, in more detail:

- $Treat_i$ is the time-invariant dummy that takes the value of 1 if the type of wine was affected by the weather shock (treatment group = Three Lakes) and 0 if it was not (control group);

- $Post_t$ is the individual-invariant dummy that takes the value of 1 if the observation came after the weather shock and 0 if it came before (cut-off date: April 2014);
- $Treat_i * Post_t$ is the interaction variable between $Treat_i$ and $Post_t$ that takes the value of 1 if the observation was part of the treatment group and came after the cut-off point, and 0 otherwise.

The coefficient of interest is β_3, which measures the difference in $Outcome_{i,t}$ between the treatment and control groups after the treatment. In a fixed-effects model, coefficient β_1 cannot be estimated due to the *within* transformation of the data. Equation (3) provides more detail, with the natural logarithm of the quantity of wine consumed as an independent variable:

$$\ln(Q_{i,t}) = \beta_0 + \beta_3(Treat_i * Post_t) + S_{i,t}\theta + Z_t\gamma + u_i + \delta_t + \varepsilon_{i,t}, \tag{3}$$

where $Q_{i,t}$ and $S_{i,t}$ (along with vector parameter θ) are the quantity and vector of control time-variant variables (mostly climatic variables), respectively, where index i designates the type of wine, and t designates the time at which it was sold. Z_t (along with vector parameter γ) is a vector of the control individual-invariant variables (mostly economic variables), and u_i is the unobserved heterogeneity across individual AOCs. The latter term cancels out due to the *within* transformation in the fixed-effect model. δ_t is the time-fixed effect (at the monthly level) and $\varepsilon_{i,t}$ the idiosyncratic error term. Note that in Equation (3), as opposed to Equation (2), the variables $Treat_i$ and $Post_t$ are not included in the model on their own (only through $Treat_i * Post_t$) due to the former's perfect collinearity with the individual FE (u_i) and the latter's perfect collinearity with the time FE (δ_t). Our regressions always use robust standard errors clustered at the individual level, which allows for autocorrelation and heterogeneity inside each cluster.

Transforming Equation (3) and deriving $\ln(Q_{i,t})$ with respect to $I_{i,t}$ (which denotes $Treat_i * Post_t$) gives us:

$$\frac{\partial Q_{i,t}}{\partial I_{i,t}} = e^{\ln(Q_{i,t})} * \beta_3 \Leftrightarrow \frac{\partial Q_{i,t}}{\partial I_{i,t}} = Q_{i,t} * \beta_3$$

We therefore obtain the semi-elasticity parameter β_3, that is to say, the percentage change in quantity relative to an absolute change in the interaction variable $I_{i,t}$:

$$\beta_3 = \frac{\dfrac{\partial Q_{i,t}}{Q_{i,t}}}{\partial I_{i,t}}$$

D. Econometric model (extension)

This subsection extends the Equation (3) model by allowing β_3 to vary over time (β^t):

$$\ln(Q_{i,t}) = \beta_0 + \beta_3^t(Treat_i * Post_t) + S_{i,t}\theta + Z_t\gamma + u_i + \delta_t + \varepsilon_{i,t} \qquad (4)$$

Autor (2003) analyzed the effects of increased employment protections on firms' use of temporary workers by including both leads and lags in a DID regression:

$$\ln(Q_{i,t}) = \beta_0 + \sum_{t=-q}^{-1}\beta_3^t(Treat_i * \delta_t) + \sum_{t=0}^{m}\beta_3^t(Treat_i * \delta_t) + S_{i,t}\theta + Z_t\gamma + u_i$$
$$ + \varepsilon_{i,t} \qquad (5)$$

We set $t = 0$ as the start of the treatment (cut-off date) with q leads $[\sum_{t=-q}^{-1}\beta_3^t(Treat_i * \delta_t)]$, which analyzes pre-trend characteristics, and m lags $[\sum_{t=0}^{m}\beta_3^t(Treat_i * \delta_t)]$, which analyzes the treatment effect changes (if any) over time after the treatment (see also Jacobson, LaLonde, and Sullivan (1993) for event study models).

The idea is to interact the time dummies (δ_t) with the treatment indicator ($Treat_i$) for the pre-treatment and treatment periods. It is important to leave out one of the treatment periods if we wish to get a saturated model. The estimated coefficients between the treatment and control groups in the pre-treatment period should be statistically insignificant to prove the common trend assumption (Karlsson, Nilsson, and Pichler, 2014). The interaction dummies after the treatment indicate whether the weather shock effect is fading, staying constant, or increasing over time. Due to the important disturbance to the monthly-frequency data, we also aggregated specifications for time and treatment interactions by trimester and semester. The results of this analysis are presented in the Robustness Checks section.

V. Results

## A. Parallel time trend: Visual evidence

Figure 2 shows retail market wine sales income by year for the Three Lakes region and the five control regions combined. The Three Lakes region shows a strong decrease in 2014 sales (corresponding to the 2013 vintage affected by the hailstorm) and a recovery back to its *normal* path in 2015. The control regions' sales seem to be on a regular path from 2012 to 2015.

The cut-off date separating the pre-post weather-shock effect periods was set at April 2014 in the knowledge that 2013's first vintages should have been entering the retail market at that moment. The period under analysis ends in March 2015, just before April 2015 when 2014's first vintages should have appeared on Swiss supermarket shelves. Figure 3 shows the monthly sales quantities and the regression model results of those quantities (sums for treatment and control groups at each time point) over time. The vertical line indicates the cut-off date (April 2014). It is interesting to note that, as visual evidence, before the cut-off point, the two groups
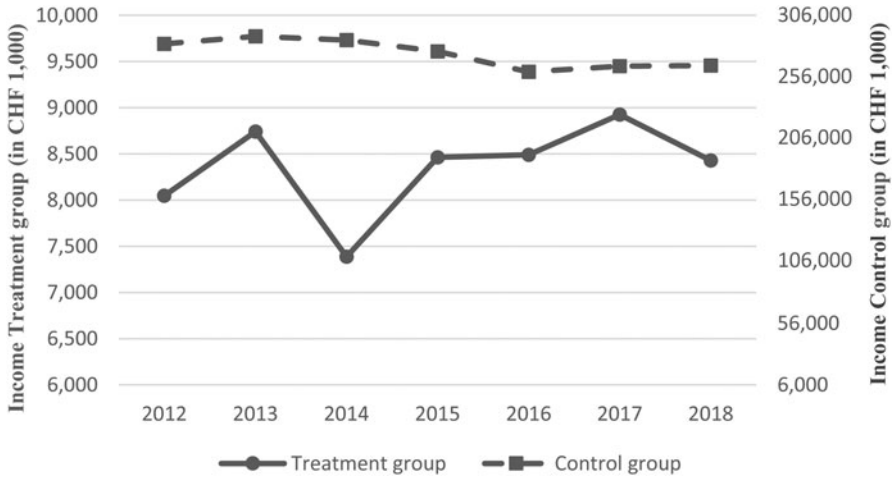
Figure 2. Treatment and control regions' wine sales income.
Source: Author's illustration using data from Nielsen (2019).
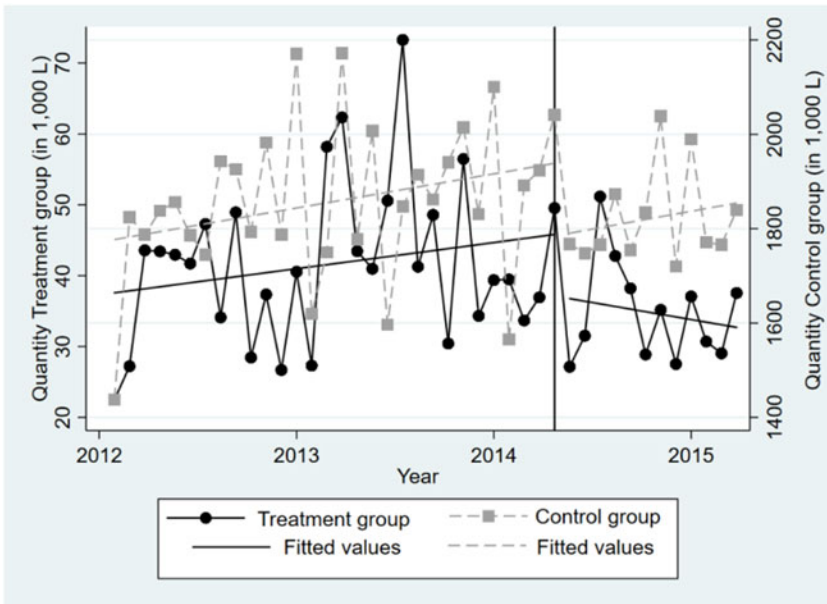
Figure 3. Time trend for sales quantities.
Source: Author's illustration using data from Nielsen (2015).

followed a generally parallel trend. We can notice that in the post-shock period, the treatment group experienced a negative trend, with a much-changed regression line slope, whereas the control group seemed to follow a similar pattern to the

Table 3 Regression results for quantity, price, and income (fixed effects)

	(1)	(2)	(3)
	$\ln(Q_{i,t})$	$\ln(P_{i,t})$	$\ln(I_{i,t})$
$Treat_i * Post_t$	−0.2277***	0.0277**	−0.2000***
	(0.0691)	(0.0135)	(0.0656)
Covariates	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Constant	−88.7061**	−24.5889***	−64.1173
	(41.5889)	(8.7366)	(35.8422)
Observations	2,319	2,319	2,319
No. of labels	70	70	70
R-squared	0.3245	0.7026	0.2375

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered robust standard errors (individual) in parentheses; FE = fixed effect (individual).

pre-treatment period. The regression results for income (*quantity * price*) with the same graph axes and configuration as Figure 3 (but not presented here), confirmed the treatment group's change to a negative slope after the cut-off date.

B. Baseline regression results

The impact of the hail weather shock on the Three Lakes region's retail sector wine sales can be broken down into a direct effect and a compensation effect. The direct effect corresponds to the sales loss due to the sharp reduction in the supply of wine. The retail sector could compensate for this reduction in two main ways: by drawing on the Three Lakes region's wine stocks or by selling more wines from the control regions. Table 3 reveals that the direct effect was larger than the compensation effect (net effect). Considering Table 3's reference Specification (1), the hail weather shock had a significant effect, reducing the treatment region's volume of wine sales in the treatment period by 22.8% compared to the control wines (statistically significant at 1% level).[7] Specification (1) includes individual FE and time FE, and the covariates are added to the regression. The Hausman test, which rejects the H_0 hypothesis that the differences in coefficients between the FE and RE models are not systematic, supports the inclusion of individual FE (through the *within* transformation of the data) in our different specifications (Hausman, 1978). When considering the anticipation effects (not presented in Table 3), we still found a similar and statistically significant effect when we moved the cut-off point backward to September 2013. This would suggest that either Swiss supermarkets started to remove Three

---

[7] In order not to bias the regression results, we removed three individual treatment AOCs and two individual control AOCs (leaving 73 instead of 78 individual AOC wines) because their volumes were inferior to 100 liters per period.

Lakes wines (vintages prior to 2013) from their shelves before the introduction of the hail-affected 2013 vintage or that consumers had already included information on the weather shock into their demand functions. This econometric result (–22.8%) from the retail market was consistent with the Three Lakes region's 24% lower sale volume across all distribution channels, as discussed later. It therefore seems that there were no diversification effects in wine sales as private consumers (direct sales), restaurants (HoReCa), and wholesalers all showed very similar negative trends to supermarkets for the affected region.

To examine the anticipation effect in supermarkets related to the hail weather shock, we considered the cross-price elasticities between the Three Lakes region and the other five Swiss wine regions and foreign wines by color. After removing a share of Three Lakes wine from their shelves, supermarkets would be more likely to replace them with Swiss or foreign wines that had positive, statistically significant, cross-price elasticities. According to our estimates, Three Lakes red wines were substitutable with red wines from Geneva, Ticino, and France. Three Lakes white wines were substitutable with white wines from Valais, Geneva, Italy, and the rest of the world. Three Lakes rosé wines were substitutable with rosé wines from Vaud, France, and Spain.

Table 3's Specification (2) shows the results of the treatment effect on the price of the Three Lakes region's wines sold on the retail market. The weather shock's price effect was statistically significant (at the 5% level) and was +2.8%, as one would expect from an exogenous supply shock. As explained before, a negative supply shock should have resulted in a reduction in the quantities of wine put on the market, which should have been accompanied by price rises. The regression results confirmed this expected theoretical effect, which mostly involved lower sales of the treatment region's wines. As mentioned previously, Ginsburgh, Monzak, and Monzak (2013) showed that the *hail* variable, which measured the number of days of hail in April, had a significantly strong negative influence on prices. This result seems counterintuitive with regards to our findings (hail's strong positive impact on wine prices), but the data and the contexts are completely different as we used supermarket data instead of data from châteaux. Individual wine producers' reputations hold relatively little sway in Switzerland. Regional reputations are more important and the collective reputation of the Three Lakes region's wines is quite low as it could not be compared to Médoc (Bordeaux, France), for example. The price segmentation of Swiss wines is very different from that of Médoc wines, which are strongly influenced by their châteaux status (Malter, 2014). Our focus was thus on the hail shock's effects on sales and prices in the Swiss retail market. Swiss wine sales are generally less related to specific vintages or to wines for aging. In the case of châteaux in Médoc, which are very focused on quality, hail shock information might lower the demand for a specific château and cause its price to drop. A hail shock can also cause phytosanitary problems later in the grape's maturation process (Corsi and Ashenfelter, 2019), but according to République et Canton de Neuchâtel (2013), even if the grapes ripened relatively slowly after the hail, their quality at harvest time was very respectable.

Table 3's Specification (3) shows the results of the treatment period's treatment effect on the income ($Q_{i,t} * P_{i,t}$) from the treatment region's wines sold on the retail market. The weather shock's income effect was –20.0% (statistically significant at the

Volume (1,000 L)
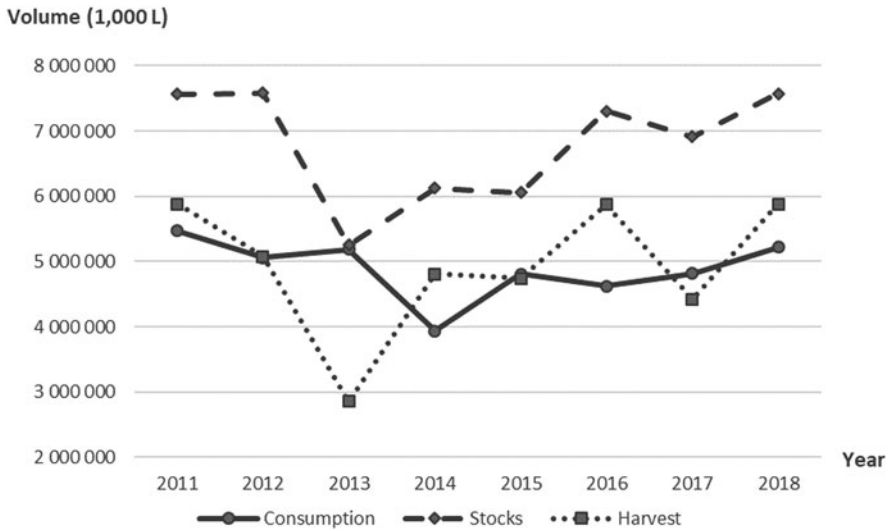
Figure 4. Consumption of wine from the treatment group.
Source: Author's illustration using data from FOAG (2019).

1% level). It is interesting to note that sales income, which includes both quantity and price, shows a reduction in Swiss retail market profits. It seems, therefore, that higher prices did not compensate for the lower quantity of wine sold, confirming a net loss in income from Swiss retail market sales for Three Lakes wines due to the 2013 weather shock.

Looking back at the whole Swiss wine market in 2013, we can see that consumption of the treatment region's wines was quite stable due to a lowering of stocks (Figure 4). However, the Three Lakes wine consumption experienced an important fall in 2014 (–24%), which corresponded to the same specification of our model for the Swiss retail market. In 2015, consumption seemed to come back to its initial levels, and this positive trend continued from 2016 to 2018 (FOAG, 2019).

The retail market's evolution after 2015 seemed to be quite similar for the Three Lake region. Figure 2 shows that from 2015 to 2018, income was quite stable, even though we should note that volumes never got back up to 2013's levels (pre-treatment period). At the same time, there was a regular upward trend in prices, which partially compensated for the "persistent" reduction in wine sales volumes in the retail market. Consumers of the treatment region's wines seemed to come back in 2015 and were ready to pay higher prices, resulting in the stabilization of the Three Lakes wine region's income on the retail market.

VI. Robustness checks

To test the DID model's stability, we performed four different robustness checks on the dependent variable of sales quantities. The following analyses are based on baseline model Specification (1) (see Table 3). Thus, by default, we include the individual FE, the time FE, and all the covariates.

Table 4 Placebo pre–post treatment regressions (quantity)

	(1)	(2)
	Pre-treatment	Post-treatment
$Treat_i * Post_t$	−0.1265	0.0748
	(0.0883)	(−0.1024)
Constant	−191.3315*	−107.1857
	(92.2082)	(189.7410)
Observations	1,464	2,340
No. of labels	70	71
R-squared	0.3026	0.3287

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered robust standard errors (individual) in parentheses; FE = fixed effect (individual).

Table 5 Placebo control regions regression (quantity)

	(1)	(2)	(3)	(4)	(5)
Placebo region	Valais	Vaud	Geneva	G-CH	Ticino
$Treat_i * Post_t$	−0.0771	0.0379	0.1217	0.0642	0.1117
	(0.0497)	(0.0833)	(0.0927)	(0.0714)	(0.0746)
Constant	−81.3427**	−76.9864*	−80.5901*	−78.5024*	−95.4196**
	(−40.2871)	(−41.4338)	(−41.2078)	(−40.6861)	(−41.7297)
Observations	2,319	2,319	2,319	2,319	2,319
No. of labels	70	70	70	70	70
R-squared	0.2828	0.2970	0.2918	0.301	0.2996

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered robust standard errors (individual) in parentheses; FE = fixed effect (individual).

A. Placebo pre–post treatments

This robustness check's goal is discarding the fact that no other anticipated or post-poned effects occuring in the Three Lakes region. In Table 4's Specification (1), we created a placebo pre-treatment effect by anticipating the cut-off date of one year, namely in April 2013. As expected, we did not find any significant statistical results. This confirmed that no pre-treatment effects occurred. We also created a placebo post-treatment effect—Specification (2)—by moving the cut-off date to one year later in April 2015. As expected, even though this coefficient became positive, we found no significant statistical results. This seems to confirm that the treatment effect was fading.

B. Placebo control regions

Table 5 shows the results from our five placebo treatment regions. This analysis is important for demonstrating that the common trend assumption (Karlsson, Nilsson, and Pichler, 2014) is not violated by one of the five control regions. One

example of a violation of that assumption could be a significant supply shock in one of the treatment regions. In this regression model, we removed the Three Lakes region and treated each control region in turn as a placebo treatment region against the four remaining controls. As expected, we found no statistically significant results, and this model seemed to show that there were no significant supply shocks for any of the control regions in the same treatment period framework chosen for the Three Lakes.

C. Regressions for different configurations of the control group

This robustness check's goal is to change the control group's specification, removing one of the five regions at a time from each regression. The region's sizes varied a lot in terms of the quantity of wine they sold. Therefore, it is important to check whether removing one region from the regression would change the results significantly. Table 6 shows that this baseline specification did not significantly change our regression results (between –21.9% and –25.8% compared to –22.8% baseline regression results). This demonstrated that the baseline model was stable, with statistically significant results at the 1% level. Another robustness check (not presented) was to create two synthetic control groups, one closer to (Valais, Vaud, and Geneva) and one farther away from (Ticino and German-speaking Switzerland) the Three Lakes region. These results showed negative effects of 23.0% for the first and 23.5% for the second synthetic control, both at the 1% significance level.

D. Regressions by color type

Finally, Table 7 presents three different cross-color specifications regressing the treatment region's wines (All, White) with the control wines (All, Red, and Rosé). The proportions of red, white, and rosé wines in each wine region vary strongly. This is an additional robustness check that considers this heterogeneity by testing whether the color of a wine can influence the baseline regression results (presented in Table 3). The results all remained significant at the 1% level and relatively stable compared to the baseline results, varying between –23.6% and –27.7%.

Table 6 Regressions for different configurations of the control group (quantity)

	(1)	(2)	(3)	(4)	(5)
Taken out	Valais	Vaud	Geneva	G-CH	Ticino
$Treat_i * Post_t$	−0.2578***	−0.2190***	−0.2197***	−0.2260***	−0.2270***
	(0.0712)	(0.072)	(0.07097)	(0.0708)	(0.0704)
Constant	−142.7845***	−92.0549*	−79.4692*	−72.7472	−113.4583*
	(47.1435)	(46.9406)	(45.0053)	(45.2509)	(57.423)
Observations	1,769	1,869	1,927	1,937	2,096
No. of labels	56	55	57	60	63
R-squared	0.3002	0.3250	0.3000	0.3221	0.3800

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered robust standard errors (individual) in parentheses; FE = fixed effect (individual).

Table 7 Regressions by color type (quantity)

	(1)	(2)	(3)
$Treat_i * Post_t$	−0.2726***	−0.2363***	−0.2765***
	(0.0826)	(0.0765)	(0.0870)
Color treatment group	White	All	White
Color control group	All	Red and Rosé	Red and Rosé
Constant	−60.3588	−107.3692	−65.2067
	(42.6202)	(−51.4292)	(−52.1732)
Observations	2,145	1,504	1,330
No. of labels	64	46	40
R-squared	0.3175	0.2894	0.2759

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered robust standard errors (individual) in parentheses; FE = fixed effect (individual).

E. Extension of the regression results

This robustness check's goal was to go beyond the pre-treatment and treatment design by analyzing the hail shock at higher frequency periods (semesters, trimesters, and months). Letting β_3^t in Equation (5) vary over time allowed us to analyze the trend in more detail and with more precise time trends. Figure 5 shows the interactions between time dummies and treatment groups over time, aggregated at the semester level. We noted that the pre-trend interactions were statistically insignificant and quite regular. The dotted vertical line indicates the date of the weather shock (June 2013). The dashed vertical line shows the 2013 vintage's arrival on the retail market (at the April 2014 cut-off point). The solid vertical line represents the end of the 2013 vintage's effect (March 2015), as the new 2014 vintages, unaffected by the weather shock, were entering supermarkets. It is very interesting to note that β_3^t, even though statistically insignificant, had a negative sign between the dashed and solid vertical lines. Meanwhile, after the 2013 vintage effect, the estimated coefficients became positive again, supporting the negative shock effect of the treatment region's wine sales in the treatment period under evaluation.

For more details, Table 8 gives all the estimated lead and lag interaction coefficients for the semestrial frequency specification. The semestrial-frequency specification seemed to be the most convincing one for analyzing a time-varying β_3^t, better than the trimestral frequency specification and far better than the monthly frequency specification, which gave less clear visual evidence.[8]

VII. Conclusion

By exploiting the occurrence of a unique natural experiment, namely a hail weather shock in the Three Lakes wine region in 2013, we were able to estimate statistically significant negative effects on wine purchases from that region in the Swiss wine retail

---

[8]Detailed results about trimestral frequency and monthly frequency specifications are not reported here but are available from the author upon request.
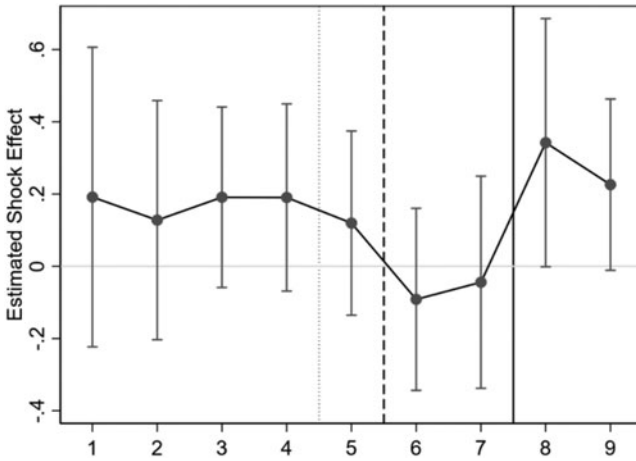
Figure 5. Estimated shock effect over time (by semester).
Source: Author's illustration using data from Nielsen (2015).

market. We used a unique dataset from the Nielsen Company that provided quantity and price information for different types of Swiss wine in the retail market. Using a DID regression methodology, we found statistically significant negative effects. Considering Table 3's reference Specification (1), the hail weather shock (represented by a 43.7% drop in 2013's harvest compared to 2012) had a significant effect after the treatment cut-off date of April 2014, lowering the treatment region's wine sales by 22.8% and raising its wine prices by 2.8% compared to the control wines. Looking at the income effect, we observed a 20% reduction, but the tendency seemed to move back to "normal" in 2015 and on to 2018 (see Figure 4).

We observed strong visual evidence of a parallel trend assumption between the treatment group and the control group before the weather shock, which enabled us to use the DID framework. This identification strategy was the most appropriate in our specific situation, considering our data's longitudinal structure. Several robustness checks, such as placebo pre-post treatments, creating placebo treatment regions, removing some control regions or wine colors, all helped to confirm the validity and stability of our results. The results are therefore important as they could contribute to estimating the economic effects of future weather shocks. In particular, this study could help cantonal and federal agricultural departments, professional associations, and Switzerland's wine producers to take appropriate economic policy decisions when a supply shock occurs in this specific market.

Concerning the DID framework's internal validity, we are quite confident that this exogenous weather shock, after *controlling* for several confounding covariates, was quite close to the true causal effect. Regarding its external validity, the DID model could be applied again should a similar weather shock occur in a specific wine region. Indeed, this could also be the case for other agricultural commodities if we were to use different econometric specifications about the market's distribution policies. The present results allowed us to quantify the Three Lakes region's reduction in

Table 8 Leads and lags (semester)

Leads and lags	Event	Coefficients
$t-5$		0.1916
		(−0.2489)
$t-4$		0.1277
		(−0.1987)
$t-3$		0.1912
		(−0.1500)
$t-2$	Hail shock	0.1905
		(−0.1555)
$t-1$		0.1196
		(-0.1529)
$t0$	Vintages 2013	−0.0916
		(−0.1513)
$t+1$		−0.0442
		(−0.1762)
$t+2$	Vintages 2014	0.3423
		(−0.2062)
$t+3$		0.2261
		(−0.1423)
Observations		3,465
No. of labels		71
R-squared		0.2892

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; clustered robust standard errors (individual) in parentheses; FE = fixed effect (individual).

sales income in 2014, and this could have several policy implications. For example, estimating an annual premium calculation for hail insurance (or other weather shocks) and the economic viability of investing in anti-hail nets at the producer level. Another policy example might be the development of a weather shock wine reserve for Switzerland, which would be able to defer the commercialization of a certain volume of wine and release it onto the market in years of shortages, such as in 2014, to limit price rises.

References

Angrist, J. D., and Pischke, J.-S. (2008). *Mostly Harmless Econometrics: An Empiricist's Companion.* Princeton, NJ: Princeton University Press.

Ashenfelter, O. C. (1978). Estimating the effect of training programs on earnings. *Review of Economics and Statistics*, 60(1), 47–57.

Ashenfelter, O., and Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *Review of Economics and Statistics*, 67(4), 648–660.

Ashenfelter, O., Ciccarella, S., and Shatz, H. J. (2007). French wine and the U.S. boycott of 2003: Does politics really affect commerce? *Journal of Wine Economics*, 2(1), 55–74.

Autor, D. H. (2003). Outsourcing at will: The contribution of unjust dismissal doctrine to the growth of employment outsourcing. *Journal of Labor Economics*, 21(1), 1–42.

Card, D., and Krueger, A. B. (1994). Minimum wages and employment: A case study of the fast-food industry in New Jersey and Pennsylvania. *American Economic Review*, 84(4), 772–793.

Corsi, A., and Ashenfelter, O. (2019). Predicting Italian wine quality from weather data and expert ratings. *Journal of Wine Economics*, 14(3), 234–251.

Delaquis, P., Maurer, C., Mondoux, A., and Planquart, A. (2015a). Rapport Marché suisse des vins, Rapport N02. Nyon, Switzerland: Observatoire suisse du marché des vins (OSMV), Changins, Haute école de viticulture et oenologie.

Delaquis, P., Maurer, C., Mondoux, A., and Planquart, A. (2015b). Rapport Marché suisse des vins, Rapport N04. Nyon, Switzerland: Observatoire suisse du marché des vins (OSMV), Changins, Haute école de viticulture et oenologie.

Dobis, E., Reid, N., Schmidt, C., and Goetz, S. J. (2019). The role of craft breweries in expanding (local) hop production. *Journal of Wine Economics*, 14(4), 374–382.

FOAG (2014). *Année viticole 2013.* Federal Office for Agriculture, Statistiques Vitivinicoles, Liebefeld, Switzerland. Available at https://www.blw.admin.ch/dam/blw/fr/dokumente/Nachhaltige%20Produktion/Pflanzliche%20Produktion/Weine%20und%20Spirituosen/Weinwirtschaftliche%20Statistik/2013.pdf.download.pdf/L'ann%C3%A9e_viticole_2013_statistique_vitivinicole.pdf.

FOAG (2016). *Année viticole 2015.* Federal Office for Agriculture, Statistiques Vitivinicoles, Liebefeld, Switzerland. Available at https://www.blw.admin.ch/dam/blw/fr/dokumente/Nachhaltige%20Produktion/Pflanzliche%20Produktion/Weine%20und%20Spirituosen/Weinwirtschaftliche%20Statistik/2015.pdf.download.pdf/L'ann%C3%A9e_viticole_2015.Statistiques_vitivinicoles.pdf.

FOAG (2019). *Année viticole 2018.* Federal Office for Agriculture, Statistiques Vitivinicoles, Liebefeld, Switzerland. Available at https://www.blw.admin.ch/dam/blw/fr/dokumente/Nachhaltige%20Produktion/Pflanzliche%20Produktion/Weine%20und%20Spirituosen/Weinwirtschaftliche%20Statistik/Das%20Weinjahr%202018.pdf.download.pdf/A4_viticole_F_29_4.pdf

FSO (2015). *Consumer prices.* Federal Statistical Office, Neuchâtel, Switzerland. Available at https://www.bfs.admin.ch/bfs/en/home/statistics/prices/consumer-price-index.html.

FTA (2015). *Foreign exchange rates.* Federal Tax Administration, Bern, Switzerland. Available at https://www.estv.admin.ch/estv/en/home/value-added-tax/accounting-vat/vat-foreign-exchange-rates.html.

Ginsburgh, V., Monzak, M., and Monzak, A. (2013). Red wines of Medoc: What is wine tasting worth? *Journal of Wine Economics*, 8(2), 159–188.

Haddad, E., Aroca, P., Jano, P., Rocha, A., and Pimenta, B. (2020). A bad year? Climate variability and the wine industry in Chile. *Wine Economics and Policy*, 9(2), 23–35.

Hausman, J. (1978). Specification tests in econometrics. *Econometrica*, 46, 1251–1271.

Imbens, G. W., and Wooldridge, J. M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, 47(1), 5–86.

Jacobson, L. S., LaLonde, R. J., and Sullivan, D. G. (1993). Earnings losses of displaced workers. *American Economic Review*, 83(4), 685–709.

Karlsson, M., Nilsson, T., and Pichler, S. (2014). The impact of the 1918 Spanish flu epidemic on economic performance in Sweden. *Journal of Health Economics*, 36, 1–19.

Lechner, M. (2011). The estimation of causal effects by difference-in-difference methods. *Foundations and Trends® in Econometrics*, 4(3), 165–224.

Lessoua, A., Mutascu, M., and Turcu, C. (2020). Firm performance and exports: Evidence from the Romanian wine industry. *Journal of Wine Economics*, 15(2), 207–228.

Malter, D. (2014). On the causality and cause of returns to organizational status: Evidence from the grands crus classés of the Médoc. *Administrative Science Quarterly*, 59(2), 271–300.

MeteoSwiss (2016). *Swiss climatic data*. Federal Office of Meteorology and Climatology, Zurich, Switzerland. Available at https://www.meteoswiss.admin.ch/home/climate/swiss-climate-in-detail.html.

Murray, K. B., Di Muro, F., Finn, A., and Leszczyc, P. P. (2010). The effect of weather on consumer spending. *Journal of Retailing and Consumer Services*, 17(6), 512–520.

Nielsen (2015). *Wine data from the Swiss retail market*. Data available for purchase at https://global.nielsen.com/.

Nielsen (2019). *Wine data from the Swiss retail market*. Data available for purchase at https://global.nielsen.com/.

OIV (2019). *Data by countries*. Paris, France: International Organisation of Vine and Wine. Available at https://www.oiv.int/en/statistiques/.

Porcelli, F., and Trezzi, R. (2019). The impact of earthquakes on economic activity: Evidence from Italy. *Empirical Economics*, 56, 1167–1206, https://doi.org/10.1007/s00181-017-1384-5.

République et Canton de Neuchâtel (2013). *Année viticole 2013*. Département du développement territorial et de l'environnement, service de l'agriculture, station viticole cantonale, encavage de l'état. Available at https://www.ne.ch/autorites/DDTE/SAGR/viticulture/Documents/Rapport%20sur%20l%27ann%C3%A9e%20viticole%202013.pdf.

Rubin, D. B. (1977). Assignment to treatment group on the basis of a covariate. *Journal of Educational Statistics*, 2(1), 1–26.

Swiss-Impex (2015). *Export and import commodity data*. Data available from https://www.gate.ezv.admin.ch/swissimpex/public/bereiche/waren/query.xhtml.

Tian, X., Cao, S., and Song, Y. (2021). The impact of weather on consumer behavior and retail performance: Evidence from a convenience store chain in China. *Journal of Retailing and Consumer Services*, 62, 102583, doi: 10.1016/j.jretconser.2021.102583.

Turvey, C. G., Weersink, A., and Chiang, S.-H. C. (2006). Pricing weather insurance with a random strike price: The Ontario ice-wine harvest. *American Journal of Agricultural Economics*, 88(3), 696–709.