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Estimating the Demand for Wine Using Instrumental Variable Techniques*

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Abstract

The demand for wine is generally estimated on an aggregate level as a single commodity. However, as recent history shows us, the demand for wine not only varies considerably by varietal, but also by price point within each varietal. As a result, although estimates of the demand for wine may be beneficial to the wine industry as a whole, they provide little benefit to individual wine producers. Using scan data of purchases from US retail chain stores, this paper uses store keeping unit (sku) level data to overcome the limitations of prior research on the demand for wine by providing estimates for the demand for wine by varietal and price point. We also provide estimates of own price effects, income effects by color, varietal and price segment. Problems of endogeneity inherent in demand estimation are corrected by utilizing a novel instrumental variable technique using grape prices as the instrument. (JEL Classification: C23, D12)

I. Introduction

The purpose of this paper is to investigate the demand for wine and provide insight into the behavior of U.S. wine consumers. We use a unique data set consisting of pooled cross sectional data on the price paid and number of cases sold of wine at the store keeping unit (sku) level. The data set allows us to disaggregate the demand for wine by color, varietal and price segment. We use a fixed effects model and correct for endogeneity by using an obvious yet novel instrument, grape prices, to identify the demand for wine. The paper also provides estimates of own price and income elasticities by color, varietal and price segment.

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II. Review of Literature

Most of the earlier research on the alcohol consumption aggregate wine with beer and spirits into a single category of alcohol, Baltagi and Griffin (1995 and 2002), and Grossman, Chaloupka and Sirtalan (1998), or disaggregate alcohol consumption into the three categories of wine, beer and spirits Nelson (2003). These studies generally examine time series data or pooled state level time series data and use past consumption as an instrument for current consumption. Two studies, Folwell and Baritell (1978) and Pompelli and Heien (1991), use household survey data to examine consumption specific to wine. Finally, Buccola and VanderZanden (1997) use in store scanner data similar to ours, however, only obtain data from retail chains in Portland Oregon. Nevertheless, Buccola and VanderZanden (1997) do disaggregate their data into four categories: Red wine from Oregon, white wine from Oregon, red wine from California and white wine from California.

III. Data

The wine data used for this research is Nielsen Scantrack data consisting of a cross section of sku (store keeping unit) level monthly purchases of wine scanned at U.S. retail outlets over the years 2002–2005. The data consists of average price and quantity by month of total US wine sales of foreign and domestic wine at food and drug stores with sales over $2 million dollars per year. We focus on cases of traditional glass, 750 ml bottles. The benefit of scan data is that it represents actual purchases of wine by consumers and is reflective of the demand for wine. The drawback of scan data is that it only reflects purchases in major U.S. retail chains and does not represent wine sold on premise at wineries, purchases through wine clubs or purchases at restaurants. Income is measured using US national monthly per capita disposable income taken from the BLS (Bureau of Economic Analysis, 2002–2005). The grape price data comes from the Grape Crush reports published by the California Department of Food and Agriculture and contains the price per ton and number of tons sold of wine grapes by varietal in each district in California for the years 1999–2005 (California Department of Food and Agriculture, 2000–2006).

IV. The Model

To estimate the demand for wine, we begin with a basic fixed effects model where the demand for wine is of the form:

$$\text{Cases}_{ijt} = \beta_0 + \beta_1 \text{Price}_{ijt} + \beta_2 Income_{jt} + \sum_t \delta T_t + u_{ijt} \quad (1)$$

where $Cases_{ijt}$ represents the number of cases of wine of type i (color or varietal) sold in month j and year t.
$Price_{ijt}$ represents the price of wine type i, sold in month j and year t.

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$Income_{jt}$ represents per capita disposable income in month j and year t.
T_t represents the fixed effect for year t.

Estimating demand inevitably raises questions about endogeneity and identification. Following Hausman (1978), we find the presence of simultaneity between the price per bottle of wine and the number of cases sold.[1] To correct for endogeneity we instrument the price of wine using grape prices. The price of grapes seems to be the most obvious choice of instruments for the price of wine. Intuitively, grape prices appear uncorrelated with the error term in the demand for wine and as the primary ingredient in a bottle of wine, should be highly correlated with wine prices. Unfortunately, correlations between the price of wine and the price of grapes show little relationship. This is not too surprising given the variation in the price of wine across as well as within varietals. In addition, while grapes are the primary ingredient in a bottle of wine, they account for only about 10% of the price of the average bottle of wine.[2] Nevertheless, of the costs associated with the production of wine, grapes seem a logical choice and appear to be the most tractable.

To illustrate the problems associated with correlating wine and grape prices, we summarize the data used in this study below. Summary statistics for both the price of wine and grapes are shown in Table 1.

The price of wine in our sample varies from 80 cents for a single 750 ml bottle to just under $220. However, most wines defined as those falling between 10th and 90th percentiles range from $5–$20 per bottle.

The prices of grapes in California, on the other hand, vary from $1 per ton to over $26,000 per ton depending on varietal and the district grown. Most grapes, defined again as those falling between the 10th and 90th percentiles, sold for between $350 and $3,000 per ton. Because of the wide variation in grape prices across regions and varietal in California, we are fairly sanguine about using California grape prices as an instrument for all grape prices.

Table 1
Descriptive Statistics for Wines and Grapes

	Price Per Bottle of Wine	*Price Per Ton of Grapes*
Mean	11.70	1,708.91
Minimum	0.80	1.00
Maximum	218.46	26,500.00
10th Percentile	5.25	350
90th Percentile	20.15	3,263
Standard Deviation	8.18	1,327.12
Observations	128,552	44,817

[1] The Hausman test statistic is positive and statistically significant at the 1% level.
[2] This is according to a wine industry report published by Gomberg-Frederickson (2005) which breaks down the cost of a $13 bottle of wine as follows: grapes 11%, bottling and packaging 5%, wine making 10%, winery profit, marketing and overhead 19%, distribution 23% and retail markup 32%.

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To correlate grape prices with wine prices we use the "bottle price rule" which states that the price per ton of grapes in a bottle of wine is roughly one hundred times the bottle price of the wine.[3] We then categorize the wine data into six commonly used industry price segments shown in Table 2.[4] Next, we find the mean price of grapes within each price segment, by color, varietal and year and correlated them with wine of the same price segment, color and varietal in each year. Because of the large number of varietals contained in the data, we focus only on the six biggest selling red varietals and six biggest selling white varietals. The list of varietals is shown in Table 3.

Tables 4 to 6 show the simple regressions between wine and grape prices for all wines and by varietal. As the tables show, the correlation between the price of wine and grapes is significant for all varietals and relatively strong with a coefficient of determination ranging from .51 to .91.

Given the results shown in Tables 4–6, we are confident that grape prices satisfy the requirements for an efficient instrument. The functional form of the instrument used in the demand estimation is:

$$Price_{it} = \alpha_0 + \alpha_n \sum_{n=1}^{3} PriceGrapes_{i,t-n} + v_{it} \quad (2)$$

Table 2
Price Segments for Wine and Grapes

Price Per 750ml Bottle	*Prices Per Ton of Grapes*
Under $3	Under $300
$3 – Under $7	$300 – Under $700
$7 – Under $10	$700 – Under $1,000
$10 – Under $15	$1,000 – Under $1,500
$15 – Under $25	$1,500 – Under $2,500
$25 and above	$2,500 and above

Table 3
Sample Size by Varietal

Red Wines		*White Wines*	
Varietal	Observations	Varietal	Observations
Cabernet Sauvignon	30,274	Chardonnay	37,191
Merlot	30,090	Sauvignon Blanc	9,734
Syrah	12,490	Pinot Grigio	7,399
Pinot Noir	9,882	White Zinfandel	4,094
Zinfandel	7,815	Riesling	3,959
Malbec	1,405	Chenin Blanc	1,420

[3] The "bottle price rule" is a wine industry standard and is generally attributed to grape grower Andy Beckstoffer of Beckstoffer Vineyards.

[4] These price points are used by the Nielsen Company, among others, to categorize wines.

where $Price_{it}$ represents the price of a bottle of wine of type i in year t. Since wines sold in year t are produced from grapes of the preceding year and age of the wines varies we use an average lag of three periods for the price of grapes.

Table 4
Correlation Between Wine and Grape Prices

	Dependent Variable Price of Wine
Price of Grapes	0.009**
	(772.9)
Constant	0.865**
	(53.7)
Observations	155591
R-squared	0.79

Huber-White robust t-statistics in parentheses; significance level 1% (**)

Table 5
Correlation between Wine and Grape Prices by Varietal
- Red Wines -

	Dependent Variable: Price of Wine					
	Cabernet Sauvignon	*Merlot*	*Syrah*	*Pinot Noir*	*Zinfandel*	*Malbec*
Price of Grapes	0.01**	0.009**	0.011**	0.009**	0.009**	0.009**
	(296.1)	(514.7)	(113.5)	(287.4)	(258.2)	(84.9)
Constant	0.796**	1.065**	–0.157	1.8**	1.477**	0.989**
	(14.6)	(46.9)	(1.5)	(36.5)	(30.1)	(9.8)
Observations	30262	30078	12478	9870	7803	1388
R-squared	0.74	0.90	0.51	0.89	0.90	0.84

Absolute Huber-White robust t-statistics in parentheses; significance level 1% (**)

Table 6
Correlation between Wine and Grape Prices by Varietal
- White Wines -

	Dependent Variable: Price of Wine					
	Chardonnay	*Sauvignon Blanc*	*Pinot Grigio*	*White Zinfandel*	*Riesling*	*Chenin Blanc*
Price of Grapes	0.009**	0.009**	0.009**	0.009**	0.009**	0.01**
	(596.1)	(224.9)	(222.7)	(164.1)	(165.1)	(87.7)
Constant	0.78**	1.459**	0.94**	1.19**	1.372**	0.76**
	(41.3)	(35.3)	(23.6)	(27.6)	(27.1)	(9.7)
Observations	37179	9722	7387	4094	3926	1404
R-squared	0.91	0.84	0.87	0.87	0.87	0.85

Absolute Huber-White robust t-statistics in parentheses; significance level 1% (**)

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V. Results

We begin with an analysis of the demand for all wines defined by the 12 varietals of red and white wines used in the sample. Double log specification is used to normalize the price and quantity data as well as to correct for any non-linearity in the demand functions. An added benefit of the double log regression is that all estimated coefficients can be interpreted as elasticities so that demand functions can more easily be compared across color, varietal and price segment. As shown in Table 7, OLS and IV regressions yield similar results. The coefficient on price for both models is negative and statistically significant at the 10% level representing a confirmation of the law of demand. Note also that regression results using both OLS and IV regression indicate a price elasticity of demand greater than one. The coefficients on income for both OLS and IV estimates are again similarly positive and significant indicating the normality of wine as defined by economic theory. Furthermore, both estimates indicate an income elasticity of approximately 1.5.

Next we disaggregate the data to examine the difference in demand between red and white wines. Table 8 shows IV regression results for all the wines in the sample by color. Both price coefficients are significantly different from zero. The values suggest a greater price elasticity for red wines.

On the other hand, with a value of 2.3 the estimated income elasticities for white wine are substantially higher (and more statistically significant) that those for red wine. Thus, as we disaggregate the data we begin to see a difference between the demands for red and white wines: For the wines examined, red wines are more price elastic but less income elastic than white wines.

Table 7
OLS vs. IV Regression Results for Wine Demand
- All Wines -

	OLS	*IV*
Price	−1.158**	−1.232**
	(106.8)	(108.3)
Income	1.544**	1.515**
	(3.7)	(3.6)
Year 1	−0.087**	−0.089**
	(3.7)	(3.8)
Year 2	−0.123**	−0.125**
	(3.3)	(3.3)
Year 3	−0.042	−0.043
	(0.9)	(0.9)
Constant	−9.93*	−9.449*
	(2.3)	(2.2)
Observations	128552	128541
R-squared	0.08	0.08

Absolute Huber-White robust t-statistics in parentheses; significance level 1% (**), 5% (*)

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Table 8
IV Regression Results for Wine Demand
- Red Wine and White Wine -

	White	*Red*
Price	−1.016**	−1.277**
	(48.7)	(95.2)
Income	2.354**	0.888+
	(3.6)	(1.7)
Year 1	−0.036	−0.121**
	(1.0)	(4.1)
Year 2	−0.095	−0.148**
	(1.6)	(3.1)
Year 3	−0.079	−0.03
	(1.0)	(0.5)
Constant	−18.654**	−2.651
	(2.7)	(0.5)
Observations	63712	76784
R-squared	0.04	0.1

Absolute Huber-White robust t-statistics in parentheses, *significance level 1% (**), 5% (*), 10% (+)

As Costanigro, McCluskey and Mittelhammer (2007) note, because the demand for wine is highly segmented into different price brackets, estimating a single demand function across price points results in aggregation bias.[5] To correct for this and to show how demand varies across price points, we disaggregate the data into two price segments by color (red and white): Wines below $10 and wines $10 and above. We chose $10 as our break point for two main reasons: First, $10 is still considered by many to be a psychological threshold for wine purchases. Second, breaking wine into segments below $10 and $10 and above results in relatively even sample sizes of the two groups. Table 9 shows the regression results for red and white wines in both price categories.

Consider first the estimate price elasticities. For white wines, the estimated price elasticities are negative and statistically significant in both price categories. Furthermore, for white wine, the price elasticities decrease from the lower to upper price categories. For the red wines, the estimated price elasticities are all negative and statistically significant in both price categories as well. However, in contrast to white wine, the estimated price elasticities for red wine increase as one moves up to the higher price category.

The estimated income elasticities are positive for both red and white wines in both price categories. However, while the estimated income elasticities are statistically significant for all white wines, the estimated income elasticities for the red wines are only significant for the high priced segment. For both red and white wines, the income elasticities increase as one moves up the price categories. However, the income elasticities for the white wines consistently show significantly larger coefficients.

[5] Costanigro, McCluskey and Mittelhammer (2007) determine different price segments empirically.

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Table 9
Wine Demand by Color and Price Segment: IV Regression Results

	White		*Red*	
	$10 & Under	*Over $10*	*$10 & Under*	*Over $10*
Price	−1.096**	−0.688**	−1.053**	−1.154**
	(21.3)	(13.2)	(24.1)	(44.4)
Income	2.299*	2.58**	0.609	1.244
	(2.5)	(2.6)	(0.8)	(1.9)
Year 1	0.015	−0.148**	−0.081	−0.155**
	(0.3)	(2.7)	(1.7)	(4.2)
Year 2	−0.007	−0.24**	−0.113	−0.179**
	(0.08)	(2.69)	(1.53)	(2.97)
Year 3	0.023	−0.221	−0.022	−0.036
	(0.22)	(1.95)	(0.24)	(0.47)
Constant	−18.128	−22.162*	−0.137	−6.77
	(1.9)	(2.1)	(−0.0)	(−1.0)
Observations	31420	20337	38241	38543
R-squared	0.01	0.01	0.01	0.05

Absolute value of robust t-statistics in parentheses; significance level 1% (**), 5% (*)

As noted above, we continue to observe different consumptive behavior between red and white wines. To begin with, white wine consumers are more price-responsive at the lower price point than the upper price point. First, red wine consumers are slightly more price-responsive in the upper segment. Additionally, the wine demand for red and white wine is sensitive in the upper price bracket. However, white wine consumers are nearly twice as income-responsive as red wine consumers in either price segment.

We now disaggregate the data into varietals. Regressions results for the six red wines examined are shown in Table 10. Note first that the estimated price elasticities are all negative and statistically different than zero. The two most popular red wines, Cabernet Sauvignon and Merlot, produce price elasticities close to one at 1 and 1.2, respectively. Syrah and Zinfandel exhibit the greatest price elasticities at approximately 1.7 for both. With values of less than one, Malbec shows the most inelastic price estimates. While the estimated income elasticities are all positive, only the Pinot Noir estimates exhibit results statistically different from zero.

Estimates for white wines are shown in Table 11. For the wines examined, all the estimated price elasticities are negative and statistically different from zero at the 1% level. Furthermore, all price elasticities are greater than one except White Zinfandel. The estimated income elasticities are all positive with only Pinot Grigio and Riesling statistically significant at the 5% level and Chardonnay and Sauvignon Blanc significant at the 10%.

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Table 10
Wine Demand by Varietal: IV Regression Results for Red Wines

	Cabernet Sauvignon	*Merlot*	*Syrah*	*Pinot Noir*	*Zinfandel*	*Malbec*
Price	−1.10**	−1.30**	−1.90**	−1.40**	−1.72**	−0.49**
	(52.54)	(49.38)	(43.62)	(34.16)	(34.98)	(3.40)
Income	0.72	−0.43	1.12	4.99**	0.65	0.03
	(0.76)	(0.44)	(0.84)	(3.55)	(0.40)	(0.01)
Year 1	−0.10	−0.10	−0.20*	−0.23**	−0.04	−0.12
	(1.85)	(1.73)	(2.46)	(2.86)	(0.39)	(0.65)
Year 2	−0.13	−0.10	−0.26	−0.32*	−0.02	0.08
	(1.46)	(1.14)	(2.10)*	(2.50)	(0.16)	(0.29)
Year 3	0.01	−0.06	−0.17	−0.09	0.13	0.38
	(0.09)	(0.52)	(1.09)	(0.55)	(0.69)	(1.09)
Constant	−1.28	11.35	−3.84	−45.48**	0.83	3.55
	(0.13)	(1.10)	(0.27)	(3.09)	(0.05)	(0.11)
Observations	24716	23808	10588	9263	7075	1334
R-squared	0.1	0.09	0.14	0.13	0.15	0.04

Absolute value of robust t-statistics in parentheses; significance level 1% (**), 5% (*)

Table 11
Wine Demand by Varietal: IV Regression Results for White Wines

	Chardonnay	*Sauvignon Blanc*	*Pinot Grigio*	*White Zinfandel*	*Riesling*	*Chenin Blanc*
Price	−1.14**	−1.81**	−1.36**	−0.96**	−2.09**	−2.56**
	(42.2)	(30.9)	(14.8)	(11.2)	(20.6)	(13.0)
Income	1.68	3.02	4.54*	1.19	4.69*	4.36
	(1.8)	(1.9)	(2.1)	(0.5)	(2.2)	(1.0)
Year 1	−0.16	−0.02	−0.08	0.07	−0.12	0.01
	(1.3)	(0.2)	(0.7)	(0.6)	(1.0)	(0.0)
Year 2	−0.11	−0.19	−0.18	0.13	−0.05	0.20
	(1.3)	(1.3)	(0.9)	(0.6)	(0.3)	(0.5)
Year 3	−0.08	−0.12	−0.13	0.02	0.04	0.08
	(0.8)	(0.7)	(0.5)	(0.1)	(0.2)	(0.2)
Constant	−11.35	−24.27	−40.93	−7.27	−41.53	−37.65
	(1.2)	(1.4)	(1.8)	(0.3)	(1.8)	(0.9)
Observations	30332	8338	5345	3189	3430	1123
R-squared	0.05	0.1	0.03	0.02	0.1	0.19

Absolute value of robust t-statistics in parentheses; significance level 1% (**), 5% (*)

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Next we examine wines by varietal and price category. Consider first the six red wine varietals chosen: Cabernet Sauvignon, Merlot, Syrah, Pinot Noir, Zinfandel and Malbec. The instrumental variable regression results for the red wine varietals by price point are shown in Table 12. From Table 12 you can see that the estimated price elasticities are generally negative and statistically significant with the exception of low priced Zinfandel and Malbec varietals. The estimated price elasticities low price Zinfandel and Malbec are positive but not statistically different from zero. Furthermore, the regression results indicate that these models result in the lowest explanatory power of the models estimated. We attribute these results to the relatively small sample size of both models as well as the model specification and view these results as an avenue for future research.

The estimated income elasticities range from negative for low priced Merlot and high priced Malbec, although neither is statistically significant, to relatively large, positive and significant values for Pinot Noir. Interestingly, Pinot Noir is the only wine that exhibits statistically significant income elasticities.

Table 13 contains the instrumental variable regression results by price segment for the white wines contained in the sample: Chardonnay, Sauvignon Blanc, Pinot Grigio, White Zinfandel, Riesling and Chenin Blanc. The estimated price elasticities are again mostly negative and significant. The exceptions being high priced Pinot Grigio, high priced White Zinfandel and high priced Chenin Blanc which yield positive but statistically insignificant price elasticities. Once again we attribute these anomalous results to sample size and model specification issues.

The estimated income elasticities are all positive with only upper priced Riesling being statistically different from zero at the 5% level.

VI. Conclusion

We use individual sku level price and quantity data on wine to estimate the demand for wine. Furthermore we disaggregate the demand for wine by color, major varietal and price segment. We believe this paper provides a significant improvement in the estimation of wine demand and provides a foundation for future research investigating the demand for wine. Prior studies use aggregate data which fails to capture the differences between red and white wines and differences among varietals and price segments. We overcome endogeneity issues by using grape prices as an instrument for wine prices to identify demand. Our results are generally consistent with economic theory and confirm the law of demand. In the few instances where we get estimates contradicting the law of demand, the results are not statistically significant. We believe these anomalies can be overcome by specifying a more general model of wine consumption and plan on pursuing this research in the future. We also find that wine is a normal good as defined by economic theory. These results hold across color, varietal and price segment.

Table 12

Wine Demand by Varietal and Price Segment: IV Regression Results for Red Wines

	Cabernet Sauvignon		*Merlot*		*Syrah*		*Pinot Noir*		*Zinfandel*		*Malbec*	
	≤$10	> $10	≤$10	> $10	≤$10	> $10	≤$10	> $10	≤$10	> $10	≤$10	> $10
Price	−1.14**	−1.00**	−1.15**	−1.02**	−1.43**	−2.16**	−0.17	−1.87**	0.14	−2.25**	0.51	−2.09**
	(15.13)	(26.10)	(15.48)	(17.36)	(12.14)	(23.54)	(1.04)	(26.07)	(0.86)	(22.52)	(1.76)	(5.40)
Income	1.06	0.43	−1.20	0.73	0.57	2.25	7.05	3.88	0.20	0.63	0.77	−2.36
	(0.73)	(0.35)	(0.85)	(0.54)	(0.30)	(1.23)	(2.39)*	(2.54)*	(0.06)	(0.37)	(0.21)	(0.46)
Year 1	−0.04	−0.16*	−0.04	−0.16*	−0.20	−0.21*	−0.25	−0.21*	−0.02	−0.02	−0.18	0.06
	(0.46)	(2.31)	(0.47)	(2.22)	(1.69)	(2.00)	(1.45)	(2.49)	(0.13)	(0.16)	(0.83)	(0.17)
Year 2	−0.11	−0.14	−0.04	−0.19	−0.25	−0.28	−0.41	−0.28*	0.11	−0.06	−0.02	0.36
	(0.87)	(1.23)	(0.28)	(1.54)	(1.44)	(1.67)	(1.51)	(2.00)	(0.37)	(0.41)	(0.05)	(0.72)
Year 3	−0.01	0.03	0.01	−0.14	−0.16	−0.19	−0.30	0.01	0.31	0.07	0.31	0.61
	(0.09)	(0.23)	(0.06)	(0.94)	(0.75)	(0.91)	(0.88)	(0.06)	(0.82)	(0.34)	(0.73)	(1.03)
Constant	−4.81	1.54	19.10	−1.61	1.13	−15.01	−69.53	−32.49	2.01	2.40	−6.20	32.41
	(0.32)	(0.12)	(1.29)	(0.12)	(0.06)	(0.79)	(2.25)*	(2.02)*	(0.06)	(0.13)	(0.16)	(0.60)
Observations	12398	12318	13482	10326	6339	4249	2797	6466	2286	4789	939	395
R-squared	0.01	0.06	0.02	0.03	0.01	0.09	0.01	0.13	0	0.13	0	0.14

Absolute value of robust t-statistics in parentheses; significance level 1% (**), 5% (*)

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Table 13

Wine Demand by Varietal and Price Segment: IV Regression Results for White Wines

	Chardonnay		*Sauvignon Blanc*		*Pinot Grigio*		*White Zinfandel*		*Riesling*		*Chenin Blanc*	
	≤$10	>$10	≤$10	>$10	≤$10	>$10	≤$10	>$10	≤$10	>$10	≤$10	>$10
Price	−1.26**	−0.90**	−1.81**	−1.72**	−0.04	1.07**	−0.58**	0.29	−0.73**	−1.09**	−3.37**	0
	(18.24)	(15.01)	(12.98)	(10.35)	(0.22)	(3.02)	(4.60)	(0.91)	(3.38)	(4.10)	(10.82)	(.)
Income	1.55	1.78	2.53	3.62	4.61	4.63	0.66	4.72	3.84	6.71	3.38	7.24
	(1.19)	(1.38)	(1.07)	(1.68)	(1.66)	(1.42)	(0.28)	(0.86)	(1.40)	(2.20)*	(0.72)	(1.08)
Year 1	0.01	−0.15	0.02	−0.06	−0.01	−0.34	0.07	0.22	−0.09	−0.19	−0.02	0.12
	(0.07)	(2.16)*	(0.15)	(0.52)	(0.06)	(1.77)	(0.51)	(0.62)	(0.63)	(1.03)	(0.08)	(0.32)
Year 2	−0.03	−0.21	−0.08	−0.31	−0.11	−0.30	0.17	−0.01	−0.02	−0.08	0.22	−0.01
	(0.24)	(1.84)	(0.36)	(1.63)	(0.46)	(1.02)	(0.82)	(0.01)	(0.07)	(0.28)	(0.53)	(0.01)
Year 3	0.03	−0.209	0.01	−0.28	−0.15	−0.16	0.09	−0.26	0.07	−0.01	0.04	0.39
	(0.19)	(1.44)	(0.05)	(1.14)	(0.48)	(0.43)	(0.34)	(0.41)	(0.23)	(0.03)	(0.08)	(0.51)
Constant	−9.82	−12.97	−19.09	−30.69	−44.15	−48.21	−2.39	−47.99	−35.25	−65.73	−25.87	−74.06
	(0.72)	(0.96)	(0.77)	(1.35)	(1.52)	(1.41)	(0.10)	(0.83)	(1.22)	(2.05)*	(0.52)	(1.05)
Observations	17103	13229	4569	3769	3625	1720	2751	438	2404	1026	968	155
R-squared	0.01	0.02	0.03	0.04	0	0.01	0	0.01	0	0.08	0.18	0.07

Absolute value of robust t-statistics in parentheses; significance level 1% (**), 5% (*)

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We are interested in seeing if future research shows some of the lower priced wines to be inferior goods. Future research also plans to examine the relationship between red and white wines and among the various varietals.

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