Best-Worst Scaling: A Simple Method to Determine Drinks and Wine Style Preferences

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Abstract

Wine marketers are continually involved with measuring consumer preferences usually by means of surveys or consumer purchase panel data. In this paper we provide initial results using a relatively new and very straightforward method for measuring consumer preferences. The best-worst scaling method (also called max-diffs) simply asks consumers to look at sets of products, attributes, or other factors to be compared and choose from each set the best/most favourable and the worst/least favourable. A simple count and manipulation results in a single preference scale, where the differences may be compared as distances rather than rank order. Managerial implications of the importance of wine attributes that influence consumer drinks purchasing and wine style selection are discussed as well as suggestions for future research. The goal of this paper is to demonstrate the practical and a scholarly usefulness of this approach and present a call for replication in other markets in an ongoing manner.

Introduction

Marketers in general and wine marketers in particular must constantly work to understand and forecast consumer product preferences. Wine is a unique product with a complex series of attributes, ranging from company brand, region or country of origin, grape variety, and price, to bottle shape, label design, and vintage date. Within each of these attributes there is typically more variation than in general packaged or fast moving consumer goods. For example, most supermarkets carrying wine would have at least 300 SKUs (stock keeping units) and some would have as many as 1000. There are 100,000s of wine brands in the global market along with several dozen main grape varieties and countries of origin. Prices can range from a few dollars per bottle to many hundreds of dollars, but even in a typical supermarket the price range for wine far exceeds the range for other product categories. Understanding consumer preferences for each of these attributes and the levels within them is a complex undertaking.

There are many ways to measure consumer preferences. Most common are surveys with rankings or ratings and consumer panel data, which details individual purchases. Both of these methods have problems. Respondents to surveys do not use ratings or rankings the same way across respondents and the results are subject to a range of biases resulting in scores or ratings, which are too similar or too difficult to interpret (Cohen 2003; Cohen and Neira 2003; Finn and Louviere 1992). Consumer panel data provides powerful evidence of what consumers actually purchase, but is not suitable for testing new concepts or combinations of attributes. Consumer panel data shows what a consumer actually purchased, but may mask insight into their actual preferences; attributes or products that have bigger market share are more available for purchase and so are purchased more frequently. If five times more Chardonnay is available for sale than Sauvignon Blanc and so outsells it 5:1, does that mean consumers prefer Chardonnay, or are they just purchasing based on availability? From a strategic view, this is problematic as it gives a solid description of how things are, but is limited in providing cues for how things 'might be'.

Finn and Louviere (1992) presented a very straightforward means of producing a set of consumer preferences, which does not have the above mentioned problems. They called it Best-Worst Scaling and since then, there have been a handful of papers published using this method (Cohen 2003, Cohen and Markowitz 2002; Cohen and Neira 2003; Finn and Louviere 1992; Louviere and Islam 2004), but none in the area of wine marketing.

Our aim with this paper is to demonstrate the method using beverage types and various styles and attributes of wine as examples where this technique might be particularly useful. We first briefly review research into wine preference and some of the issues and problems faced by researchers and practitioners in this area. Next, we discuss the issues in measuring consumer preferences and review the relevant literature. We review the best-worst method literature and then describe our data collection and analysis, present and provide a discussion of the results, managerial implications and future research applications of this useful method.

Review of Literature

Much of the literature on attribute importance in wine marketing is based on surveys, where consumers respond to questions on the importance of various intrinsic and extrinsic attributes. However, unless one alternative or attribute clearly dominates, it is difficult to identify the most important attribute or most preferred product. Treating the category ratings as equal interval scales may generate different conclusions than if they are treated as ordinal scales (e.g., relying upon median or 'top box' scores). Often the differences may be statistically significant, but it is difficult to assess whether a rating of 5.6 out of 7 is meaningfully different from 5.1 out of 7. What weighting scheme to apply to category ratings, or whether to rely on the alternative with the highest top box ratings, is a well-recognized problem in the case of purchase intention scales (see Morrison 1979, Jamieson and Bass 1989). Another issue is that each attribute is frequently measured with a single item rating scale newly developed just for the survey, so the reliability and validity of the scale is unknown. Attributes are usually not measured relative to other attributes or even products which must compete for the same (necessarily limited) consumer resources. Even if they are, respondents often are not allowed to indicate that they like many (if not all!) of them. Although some individuals truly might like nearly every attribute or combination, such responses don't provide adequate discrimination to help managers identify real priorities (Finn and Louviere 1990).

As noted in the introduction, wine provides a complex set of products for the marketer to analyse. Hall and Lockshin (2000) found research on the following attributes used in wine buying behaviour, each with multiple articles: taste, type, alcohol content, age (of wine), color, price, brand, label/package, practical (usability for purpose), and region. Lockshin and Hall (2003) recently reviewed over 75 articles concerning consumer behaviour for wine. They noted that many of the studies used simple surveys with rating scales to measure consumer preference for various wine attributes. Although there was much conflicting order in the rankings of the attributes for importance, previously having tasted the wine, the price, the origin, the grape variety, and the brand name of the wine were all mentioned frequently. The authors concluded that the best means to advance understanding of which attributes and combinations led consumers to purchase a particular wine was to use either choice-based experiments or analysis of actual consumer purchases. They also discussed the strengths and weaknesses of both approaches.

For the purposes of this article, we will not discuss analysis of consumer panel data. This is a powerful technique, but has several weaknesses. First, it is expensive and only a very few wine companies can afford to obtain this data, so it will not help the majority of wineries or channel members. Second, it only allows analysis of what consumers have purchased. Patterns can be discerned, but new attributes or combinations cannot be tested. Third, there is usually not enough information about the consumers to allow for segmentation, which is necessary, especially for smaller wineries targeting niche markets.

Discrete choice modeling (Louviere and Woodworth 1983; Louviere, Hensher and Swait 2000) allows the measurement of utility (part worths) of attributes in various combinations, called product concepts. These part worths are calculated from the choices made and therefore, discrete choice is an indirect method of measuring utility or preference (Louviere and Islam 2004). This method overcomes the three problems of panel data noted above. The cost is similar to most other market research survey methods and it can yield useful information with relatively small sample sizes of 100-300 consumers, depending on the number of attributes and levels tested. It allows new attributes and combinations to be made and tested for preference. Since a survey is used, either on paper or online, other consumer characteristics can also be collected and used in the analysis. One of the problems of discrete choice when used for the wine industry, or any small sector, is that the design and analysis are complex and use sophisticated and often expensive computer programs. These are mostly provided by specialist researchers, which can also increase the cost. Another, and perhaps more serious, limitation to discrete choice models is the difficulty of interpreting the data including the inability to compare utilities across different experiments (Louviere, Hensher and Swait 2000).

The Best-Worst (BW) approach, also known as Maximum Difference Scaling, was developed by Louviere and Woodworth (1990) and first published in 1992 (Finn and Louviere 1992). Recently, Cohen and Markowitz (2002) discussed the Maximum Difference Scaling (Max:Diffs) method and presented the advantages of the method. The Best-Worst approach assumes that there is some underlying subjective dimension, such as "degree of importance" or "degree of interest" and the researcher wishes to measure the location of some set of objects along this dimension (Auger, Devinney and Louviere 2004). The respondents are provided choice sets and choose the best/most important and the worst/least important from each set (an example of a choice set is presented in Appendix 1). There is no bias in the rating scale, since there is only one option to choose something that is "most" or "least" important (Cohen and Markowitz 2002). BW models the cognitive process by which respondents identify the two items with, respectively, the most and the least of a characteristic, from designed sub-sets of three or more items.

Technically, BW models the process of picking the two items that are the farthest apart on the underlying dimension of scaling interest (hence, "maximum difference scaling"). BW produces an ordinal ranking of the items for each respondent, and an interval scale of the items based on sample or segment aggregate response (Louviere and Woodworth 1990). The method allows participants to gauge importance by multiple comparisons and they can dislike something as well as like something. The several studies cited here (Auger, Devinney and Louviere 2004; Cohen and Markowitz 2002; Finn and Louviere 1992) and our experience show that consumers find the task easy and quick to complete. The major advantage to the researcher is the simplicity of the analysis, which yields a coefficient for each choice, whether it is a brand or attribute. The coefficients are ratio level and can be directly compared, which is not true for standard rating or ranking tasks. The key issue for implementation is to design a series of choice sets that include all the items of interest and all possible comparisons an equal number of times for each respondent (Louviere and Woodworth 1990). Typically, experimental design software is used to create a balanced design.

On a more technical level, if there are k attributes to be scaled, and they are placed in C subsets, there are k(k-1)/2 "BW" pairs and k(k-1)/2 "WB" pairs associated with each subset. That means that each choice set contains k(k-1) possible choice options (namely, all the BW and WB pairs). For any given subset presented to an interviewee, he/she implicitly chooses from k(k-1) pairs. Auger, Devinney and Louviere (2004) state that the total choices over all subsets of the implied pairs will be consistent with the multinomial logit model (MNL). An approximation of the model is achieved by calculating the differences of the total best and total worst counts for each item. Thus, as long as the experimental design is balanced, simply adding of the number of times an item is chosen as worst and subtracting that from the total number of times it is chosen as best provides a scale that is about 95% as accurate as using multinomial logit to model the same data (Auger, Devinney and Louviere 2004).

Method

We provide three examples of BW data and analysis. Two examples come from data that were collected in Australia among participants in several wine seminars in Adelaide and Perth during 2004. One seminar was specifically promoted as distributing wine marketing research to industry, whilst two seminars were for accountants practicing in the wine business where the marketing presentation was one of eight presentations in a day long professional development seminar. Respondents were told of the technique and asked to fill in the survey in after the presentation. There were 81 valid responses from Australia.

The other set was collected in Israel in late 2004 on a train from Tel Aviv to Beer Sheva, where there were 159 valid questionnaires. In both studies, we presented 11 choices in 12 different choice sets and the respondents were asked to choose the "best" beverage that is most appeals to him/her and the "worst" that least appeals to him/her or the most and least favoured attribute considered while choosing wine. The items differed in each country due to the differing samples; wine aware participants Australia and less wine aware in Israel. However, the number of wineries in Israel is growing and wine consumers are becoming more sophisticated and seeking better wines. In the Australian data collection, respondents were presented with a second BW selection set, again consisting of 11 choices with 9 different wine varieties and 2 attributes of ‘particular region’ and ‘well known brand,’ in 12 different choice sets.

The design in both studies was adopted from Finn and Louviere (1992), which contains 12 sets of choices (see Appendix 2 for the choice set design). The design ensures that each wine type appeared 6 times across all the choice sets. The level of importance for each choice was determined by subtracting the number of times the wine was least important (worst) from the number of times it was most important (best) in all choice sets. The level of importance of each attribute depends on the number of respondents and in the frequency that each attribute appears in the choice sets. Hence, the level of importance of a particular attribute was transformed to a standard score. The reason for standardization is to allow comparison between different groups of respondents, where the number differs in each collection.

$$\text{Standard Score} = \frac{\text{Count}_{\text{best}} - \text{Count}_{\text{worst}}}{6n}$$

where

$\text{Count}_{\text{best}}$ = total number of times an attribute was most important

$\text{Count}_{\text{worst}}$ = total number of times an attribute was least important

n is the number of questionnaires and

6 is the frequency of the appearance of each attribute in the design

Results

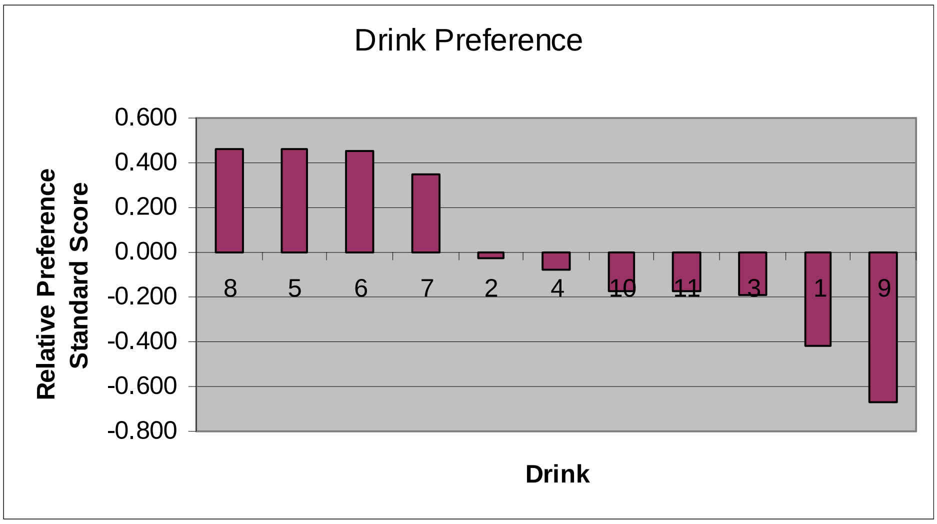
The results presented here are from initial studies undertaken to investigate and demonstrate the method and its application within the wine industry. As discussed above, the Australian data is skewed towards highly involved wine consumers and generalizations at this stage are premature as a larger sampling of low involvement wine consumers needs to be included in the data set to give a more representative sample. Table 1 presents the first of the results from the Australian study on beverage selection. The question asked of respondents was ‘please choose a wine to go with your meal’, this may have biased the results and should have been worded as ‘choose a beverage to go with your meal’. Again, these results are not being presented for generalizations, but as a demonstration of the method. ‘Level of Importance’ is the number of times respondents indicated ‘best’ less the number of times respondents indicated ‘least’, whilst the standard score, as explained in the methods section, is the level of importance divided by 6*n*, where 6 is the number of times each attribute appears in the design and *n* is the number of respondents.

Table 1: Drink Preferences in Australia (*n*=81).

Beverage #	Beverage	Level of importance (Best-Worst)	Standard Score
8	Wine from a particular variety	226	0.465
5	Premium wine	222	0.457
6	Wine from a premium region	221	0.455
7	Wine from a well known brand	170	0.350
2	Premium Beer	-14	-0.029
4	Sparkling wine	-36	-0.074
10	Soft drink	-83	-0.171
11	Natural juice	-85	-0.175
3	House wine	-93	-0.191
1	Beer	-203	-0.418
9	Pre-mix drink	-326	-0.671

Table 1 shows that the most important consumer preferred attribute is wine variety. That is to say that consumers, in this study, would rather choose their beverage based on the particular grape variety. The second most important attribute is that the wine be 'premium' wine, a result to be expected with 'house wine' the third least desired attribute for beverage selection. Supporting much of the research discussed in Lockshin and Hall (2003) is the importance to consumers of region over brand in this study. Further to the ease of analysis of this method, is the simple way results can be presented as shown in Figure 1. Each attribute is shown across the horizontal axis and the standard score on the vertical. All the attributes that received a positive score are those above the '0' line. Put simply, those with positive bar indicators are the attributes people (in this study) look for when selecting a drink to have with their meal. This is a potentially powerful advantage in both an academic and managerial sense. It enables simple communication of findings and ease of comparison from one study to another – be it a different market, cultural group or time period. It can be said that the attributes that are the least desired pose the least threat to those with the most desired attributes; using this example, pre-mix drinks (RTDs), standard beer and house wine pose the least threat to particular varietal wine, premium wine and wine from a premium region. Whilst this in itself is no startling revelation, it lends support to the use of this method in investigating wine marketing. The other key feature is that the coefficients (and standardized coefficients) can be directly compared. The first three choices are preferred about the same, while the fourth (wine from a well-know brand) is preferred less. In the lesser preferred beverages, the first two (premium beer and sparkling wine are about equal in neither being preferred or disliked, while the others are progressively less preferred. We can see the final two are strongly less preferred by this particular sample.

Figure 1: **Drink Preferences in Australia (*n*=81)**. (For drink descriptions see Table 1).



Again, these results are not presented for generalizations, but as a demonstration of the method. Highly involved wine consumers in this study have shown four attributes of high importance for beverage selection to accompany a meal, all of which are wine related (as would be expected) in order of variety-quality-region-brand, which is similar to other wine attribute choice studies. The advantage of this approach is the ease of data analysis and presentation of findings.

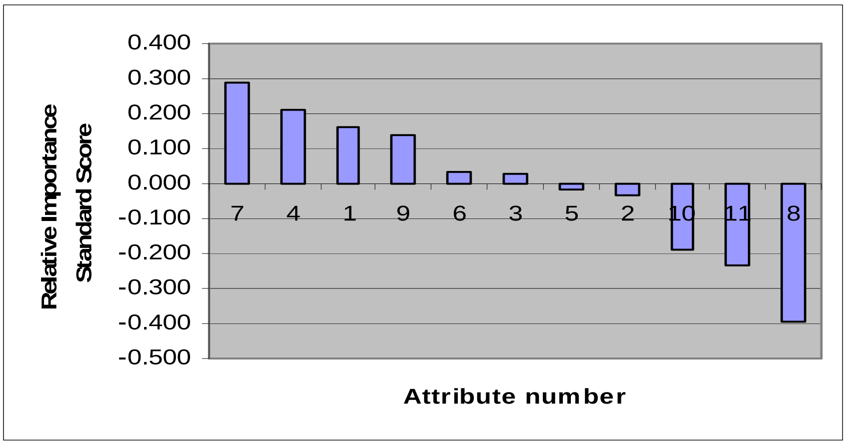
The results of the data collected using the Best-Worst method in Israel are shown in Table 2. Respondents were asked what factors were important in affecting their selection of wine for purchase. In this example it is straightforward to see how potentially useful and powerful the BW method is to investigate the complex nature of wine attributes and factors that affect purchase. Using the same design as the Australian study, 11 factors, with 12 different choice sets, the questionnaire was designed to see what insight the method could provide in terms of the factors that drive wine consumers' choice of 'which wine?' As Israel is a 'developing wine market' with a high number of lower knowledge consumers, it is interesting to see that 'recommendation' is the most important factor driving choice. Brand, variety and matching food are important to wine choice. This provides good information for cross cultural marketing, although it needs to have exactly the same choice sets and factors for comparison. It can be seen here how beneficial it would be,using this straightforward approach, to examine and compare these selection attributes across different markets, established and emerging, to look for patterns and possibly identify a 'success factor' guide to segmentation and targeting for wine marketing. We can easily see which factors are most important, which are similar and which have the least importance by far in influencing wine choice in Israel.

Table 2: Relative importance of attributes that influence consumer wine purchasing in Israel (*n*=159)

Beverage #	Attributes	Level of importance (Best-Worst)	Standard Score
7	Recommendation (friends or seller in the wine store)	277	0.290
4	Brand	204	0.214
1	Variety	156	0.164
9	Matching Food	131	0.137
6	Country of Origin	30	0.031
3	Terroir	27	0.028
5	Vintage year	-16	-0.017
2	% Alcohol	-32	-0.034
10	Health reasons	-179	-0.188
11	Medal / award	-220	-0.231
8	Label design	-378	-0.396

As in the first example, these results are shown as in graphical form (Figure 2) to demonstrate how simply the analysis can be communicated. Practitioners can easily see what is important when targeting a market such as the one in this study, as well as seeing where resources may be wasted pursuing strategies employed in other markets where they might have been successful. Although expensive printing of medal labels and commissioning of creative artwork for bottle labels may have worked in one market, in this study of wine consumers in Israel these are shown to be the least important in choosing which bottle of wine to buy. Managerially it becomes clear that an education and tasting strategy amongst restaurant and wine shop staff or even trade sales incentives are likely to have a bigger effect on sales, as it is recommendation that is the most important to the consumers in this group. Attribute 7 (recommendation), 4 (brand), 1 (variety) and 9 (food matching) are simple to identify as areas for designing strategy, whilst 8 (labeling), 11 (medal) and 10 (health reasons) are quickly seen as least important and areas least likely to impact on successful wine marketing. We can also see, as compared to the Australian results above, the attributes are different in importance. The first (recommendation) is more important than the rest and so forth through the list.

Figure 2: Relative importance of wine attributes that influence consumer purchasing wine in Israel (***n*=159**). (For attribute description see Table 2).



Both of the previous examples showed the importance of wine variety in consumers' choice of wine, as do numerous examples in the other literature reviewed by Lockshin and Hall (2003). Whilst other research methods, especially panel data, can demonstrate what varieties are chosen, Best-Worst with its speed of survey completion and simple analysis provides the opportunity for the researcher to gather this along with other attributes under investigation. Table 3 presents the results from the Australian data collection where after respondents were presented with the 12 different sets of wine styles or types.

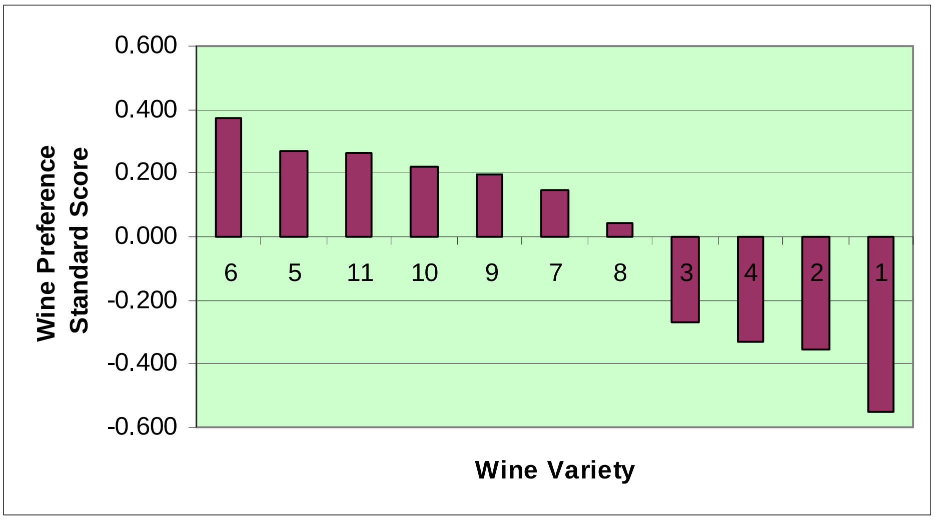
Table 3: Wine Style Preferences in Australia (*n*=81)

Beverage #	Wine Style	Level of importance (Best-Worst)	Standard Score
6	Shiraz	181	0.372
5	Cabernet Sauvignon	131	0.270
11	Wine from a Particular Region	129	0.265
10	Wine from a well known brand	106	0.218
9	Sauvignon Blanc	96	0.198
7	Cabernet/Merlot	72	0.148
8	Chardonnay	21	0.043
3	Rosé	-132	-0.272
4	Red House Wine	-162	-0.333
2	White Sparkling Wine	-174	-0.358
1	White House Wine	-269	-0.553

Although the data collected is not a large of representative sample to enable generalizations, the results shown in Table 3 provide some signals to justify collecting more data and to show how useful the insight gained using the BW method might be. Shiraz is the largest market share wine in Australia and the BW design shows it is also the most preferred wine variety, followed by Cabernet Sauvignon. Interesting is that even when mixed with specific varieties, consumers prefer a particular region, which is the third most important attribute and quite similar in preference to Cabernet Sauvignon. With more data, particularly from low involvement wine consumers, it would be interesting to see if this pattern holds, or if in fact the low involvement consumers have a markedly different pattern. The result of Sauvignon Blanc, as the 'most' positive white wine compared to Chardonnay is also interesting in this sample. Chardonnay is the largest market share white variety in the Australian market, whilst Sauvignon Blanc is a small share variety. Again, although more data needs to be collected, this lends some support to the advantage of the BW method over panel or scan data. Is more Chardonnay sold because it is a large 'brand' or is it a large brand because people like it more? This is to some extent a 'chicken or the egg' question that BW might generate some insight into. Anecdotal evidence from one of Australia's largest retailer chains shows some decline in Chardonnay sold and a marked increase in Sauvignon Blanc sales. Opportunities for further research are discussed later.

The graphical representation in Figure 3 shows that Shiraz is most preferred above all other styles. Cabernet Sauvignon and 'wine from a particular region' are equally preferred, followed by 'well-known brand' and Sauvignon Banc. It is clear that house wines and sparkling wines are not preferred types, while rosé is disliked slightly less. White house wine is by far the least preferred in this sample. The relative sizes of the bars clearly signify he strength, not just the order of preference.

Figure 3: Wine Style Preferences in Australia (***n*=81**) (for attribute description see Table 3).



Managerial Implications

Some of the managerial implications of this paper, and of the Best-Worst method, have been highlighted throughout the review of the literature and the discussion of the results. The data collected in this initial work is biased toward high involvement wine consumers and wine selection over other beverages (in the Australian data), so it is not in the scope of this analysis to make managerial implications per se. It has been shown, however, that the method itself has far ranging managerial implications and that there are signals within this research that support further research, a direction for which is discussed below. The BW approach provides a reliable method for designing and conducting research into wine marketing. Its flexibility in what is included as an attribute can go some way into the web of attributes and brands involved in wine marketing. The speed with which respondents can complete a survey is more likely to enable higher numbers of participants in any situation. The three examples used in this paper were gathered during a routine train journey amongst commuters and from executives attending seminars. Our experience is that the task is simple and not time consuming to complete.ß

The ease of design is relatively straightforward once it is understood and computer software is available to facilitate this. That said it is imperative that research be undertaken using a design of whatever number of attributes is desired. The simplicity of the analysis has a significant contribution to make both academically and managerially as simple spreadsheets are used to perform counts and generate graphs. The graphs themselves are simple and effective for communicating findings and present managers with a tool for planning and discussion. Practitioners and academics alike can see the picture quickly rather than spending valuable time to understand the numbers and results before any meaning or strategy can be formulated. Significant differences, whether statistical or not, are easily seen from the coefficients and graphs.

Further Research

The Australian data has a high number of high involvement wine consumers. This skew limits the data from being used for segmentation of high and low involvement wine consumers as other studies have done (Lockshin and Hall 2003). A new survey needs to ask questions involving a 'which beverage' choice as well as further exploration of 'which variety' or style. The investigation into variety has many opportunities for future research to benefit the wine industry as well as furthering academic research. Within the Australian market alone this work has the opportunity to extend into longitudinal research with sufficient data collected each year to build a picture of the change (or steadiness) occurring amongst consumer preferences for wine varieties and styles. This might go someway to providing some insight into production decisions, such as what vines to plant, and limit the problems with over planting particular varieties and the time lag involved in changing the production of different varieties. The BW method used this way has the potential to bring potential consumers into the market place and minimize the chance of losing existing consumers through not providing wines that are what the consumer most wants. For example, if the trend shows an increasing preference for Pinot Grigio then production of that particular variety is worth exploring.

The research conducted in Israel as to the drivers affecting consumer choice of 'which wine' warrants replication in other emerging markets, using the same attributes and choice sets, to enable comparison across cultures and markets, as well as high and low involvement. One of the aims of this paper is to attract researchers in various markets to replicate the research and join in building a market by market profile using the Best-Worst method. As has been shown in the Australian data collection, the simplicity of completion enables more than one research question to be included. Such replication could include questions concerning beverage selection, drivers affecting which wine and variety preference. This in itself is one of the better opportunities to advance the contribution of wine marketing as a discipline through bridging the gap to industry and increasing the knowledge within the discipline itself. The method could be used to explore other aspects of wine marketing such a cellar door, wine tourism and in-store locations. Once we have established the design approach to work with various attribute numbers we can then design experiments to use BW on, for example, the 4 most preferred attributes to see how they hold when compared only to each other though omitting the 'worst' preferred attributes.

Conclusion

The Best-Worst method is an approach that has much to offer wine marketing. This paper has shown three different examples of this method in use, as well as outlining the simplicity of analysis and ease of communicating the results. The results are actual distances along a preference scale, so if the designs are the same, then direct comparisons between sets of data can be made. Areas for future work include, but are not limited to, beverage preference, drivers of wine selection, demand and trend gauging of preferences for wine variety.

With a global wine market that is by and large stagnant (if not declining), the BW method and the applications outlined in this paper present an approach that may assist the industry to grow overall. Continuing this research may assist the industry through producing wines that are the style 'best' sought after (amongst existing and potential consumers), minimizing the risk of losing existing customers through not meeting their preferences as well as identifying what other beverages pose threats in different consumer segments. The methods may also help choose how to most efficiently market to wine consumers, market by market, as they choose which wine to buy. This efficiency of marketing has a strategic contribution through increasing the better utilization of resources to match the market. This paper has given a start the researchers involved here intend continuing. Hopefully through this forum they will be joined by others interested in replicating the study in their own markets, providing the wine industry with insight and assisting the development of the wine marketing discipline through knowledge growth and building international networks.

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Appendix 1: Sample of a choice set for Best-Worst questionnaire

In the following tables, please identify the MOST important issue (attribute) and the LEAST important issue (attribute) when you are choosing wine.

Check ONLY ONE issue for each of the most and least columns, in each table. Each table will have one item ticked for the MOST preferred and one item for the LEAST preferred.

Least	**Issue**	**Most**
2	Grape variety	
4	Brand	
8	Vintage year	
10	Recommendation (friends or the seller in the wine store)	

Appendix 2: Fractional factorial design for choice sets

Attribute #	Choice set #												Appearance
	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	
1			x			x	x	x		x		x	6
2	x			x				x	x	x		x	6
3		x			x		x		x	x		x	6
4	x		x				x		x	x	x		6
5			x		x			x	x		x	x	6
6				x		x	x		x		x	x	6
7		x	x	x						x	x	x	6
8	x	x					x	x			x	x	6
9				x	x		x	x		x	x		6
10	x				x	x				x	x	x	6
11		x				x		x	x	x	x		6
# of attributes in a choice set	4	4	4	4	4	4	6	6	6	8	8	8	

x the beverage appears in the choice set