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Quality production and quality indicators in intermediate products

by

A. Zago

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Angelo M. Zago

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1. Introduction

Measuring and evaluating the right attributes of raw materials, commodities, and intermediate products is a common problem in many sectors of the economy. In food industries, for instance, it is well known that the necessary condition for the making of a good wine is the availability of grapes with the right attributes.[1] The same argument can be put forth for the characteristics of milk for cheese production, of fruits for juices, of beets or canes for sugar, of beans for coffee, and many others. In addition, this problem is of interest also in other industries: for example, the quality of chips is important for the computer industry, like that of ores for steel production, of steel for construction works, and of crude oil for refined oil, just to name a few.

In this study we propose a methodology to measure the characteristics and composition of intermediate products, i.e., grapes for wine production, and we pursue three objectives. First, we characterize the technology by investigating the relationships among the different quality attributes and the production level. This objective is pursued with a systematic investigation of the disposability properties of the technology, which allows to show that some quality attributes are substitute, while others are complement in production. We also find that many

[1] Most practitioners would argue that the making of a good wine is more an art than the mere result of scientific or technological efforts. Truth is that a necessary condition to make a good wine is the use of good grapes. Indeed, an expert winemaker can obtain some decent wine even from lousy grapes, but surely she would make a much better wine from good grapes, where by good grapes we mean those with the right components and quality attributes.

of the disposability properties are not stable across years, presumably because of different weather conditions, and between crop varieties.

Second, with the methodological contribution, we address the issue of how to measure quality attributes for intermediate goods using a general representation of the technology. Although there are other instances of this problem in the literature, especially in that dealing with hedonic prices, to the best of our knowledge there are no contributions that address explicitly this topic on the production side.[2] In this paper we model the quality attributes with a multioutput technology, using a general representation of technology based on directional distance functions. These are a generalization of the radial distance functions which, since Shephard's contributions, have been used to give a single-valued representation of production relations in case of multiple inputs and multiple outputs (Chambers, Chung and Färe, 1996, 1998).

Directional distance functions indeed can be seen as an alternative and more general way to represent technology and to compare and measure input, output and productivity aggregates (Chambers, 2002). The quality aggregate measures we propose using directional distance functions may be used to evaluate firms' output taking into account the whole set of quality attributes. These alternative measures thus can be compared with the standard practice in the industry of using only one attribute, for instance sugar content used to measure the quality of grapes for wine production.

The third objective of the paper, more policy-oriented, is to evaluate how quality attributes interact with the quantity level in the production of these intermediate products. The reason for this interest is that in many agricultural markets and food industries, especially in Europe, producer groups are granted the authority to self-regulate the production and trade of many commodities. While in the US the often enforced policy for quality regulation is the use of minimum quality standards, in the European Union a more common policy device is the imposition of ceiling on yields per unit of land. This regulation is common and allowed, for instance, for those producer groups that regulate production and trade of wine with *appellation contrôllée*; for those that regulate typical products; and for those operating in fruit and vegetables industries.[3]

Advocates of this regulation claim that by reducing the production level one can in fact increase quality, and thus quantity ceilings would benefit consumers

[2] For food industries, one contribution considers food safety as a dimension of quality and represents it with a multioutput model of the technology (Antle, 2000).

[3] Respectively, UE Regulation no. 1493/99, no. 2081-2082/92, and no. 2200/96.

and producers alike.[4] In other words, output control measures would be justified because they increase economic welfare, and should not be criticized and prosecuted by antitrust authorities (Canali and Boccaletti, 1998). The fact is that the economic analysis on this topic is relatively scarce,[5] one notably exception being a paper by Arnaud, Giraud-Heraud and Mathurin (1999). In a model with vertical differentiation of the final product, i.e., wine, they are able to show that in some instances output control by a producer group can indeed increase total economic welfare. However, the results of the paper impinge on the assumption of the substitutability between quality and quantity or, put in another way, quality and quantity substitutability should be a necessary condition for the regulation to be welfare-increasing.[6]

Although this assumption on the technological relationship may appear reasonable to the reader and to many practitioners, no empirical work has established its nature.[7] In the paper we find evidence of a significant non-linear trade-off between quantity and aggregate quality for the years considered and for both varieties investigated. Moreover, for sugar and total acidity, two major quality components of grapes, for most of the years considered the trade-off with yields occurs at lower production levels in Chardonnay than Merlot.

The next section reviews the literature that addresses the issue of how to take into account quality in the production process. Then we introduce the notation, the model and the empirical implementation algorithms we use in the study. In section five we illustrate the data we use, based on production practices and output results of two relatively well known grape varieties, Chardonnay and Merlot.

[4] Indeed, "The rationale often used to justify quality regulations runs as follows: removal of off-grade product necessarily improves the average quality of the product moving to market; a higher quality product for the consumers should, presumably, command a higher price; consequently, producer returns can be enhanced by providing a higher quality product, and everybody is better off" (Jesse and Johnson, 1981: 12, in Bockstael, 1984).

[5] In the literature there is a long and controversial tradition on the welfare impact of Marketing Orders, for instance, but most of the focus has revolved around the impact of minimum quality standards (see, e.g., Bockstael 1984 and 1987; Chambers and Weiss, 1992).

[6] Thus we have that "...the result of the collective coordination of the set of producers is a direct consequence of this hypothesis. Therefore the more the increase in the supply is followed by an objective decrease in the quality, the easier it is to justify a decentralized policy of regulation of the supply. Nevertheless in practice, it is obvious that the levels reached by the technological constraint apply only within a well defined context which can be altered every year in a wine growing area..." (Arnaud *et al.*, 1999: 20).

[7] However, there is a vast literature in enology investigating these and other relationships using multivariate statistics (for a review see, e.g., Jackson and Lombard, 1993).

Section six presents and discusses the results. Section seven concludes the paper with the suggestions for further research work.

2. Review of the literature

The problem of taking into account the quality attributes of different goods has a long tradition in economics, and the most well established efforts in this direction are probably those of the hedonic pricing literature in the context of the Consumer Price Index statistics. The question in this case is how to adjust consumer (or industry) prices for increases in the quality of goods, such as computers, cars, and other durable goods (Triplett, 1990).[8]

The hedonic pricing literature uses regression techniques to relate the (market) prices of different "models" or versions of a commodity to differences in their characteristics or "qualities". The earliest references of this technique come from agricultural economics, with the early work of Waugh on vegetable prices and Vail on fertilizers (Griliches, 1990). However, to the best of our knowledge, no hedonic study has been undertaken to estimate the production technology, the main point of hedonic prices techniques being the use of market prices to identify consumers' preferences.

One of the first attempts to incorporate quality attributes in a model of producer behavior is a paper that views process and quality change as outcomes of a firm's optimization problem (Fixler and Zieschang, 1992). This contribution shows how a market-determined price-characteristics locus can be used to adjust the Tornquist output- and input-oriented multifactor/multiple output productivity indexes of Caves, Christensen and Diewert (CCD) (1982) for changes in input, output and process characteristics. Using radial distance functions, it shows how the quality adjusted indexes proposed are the product of two indexes, a quality index and a CCD-type Tornqvist productivity index.

Extending the work on productivity of CCD, Färe *et al.* (1992) define an input-oriented Malmquist productivity change index as the geometric mean of two Malmquist indexes as defined by CCD, and develop a nonparametric activity analysis model to compute productivity using linear programming. In a subsequent paper, Färe, Grosskopf and Roos (1995) extends this productivity index by incorporating attributes into the technology. Studying a panel of Swedish pharmacies, they use the attributes together with ratios of distance functions to

[8] Another vast literature deals with the valuation of enviromental quality (see, e.g., Bockstael, Hanemann and Kling, 1987).

measure the service quality of each pharmacy. By further imposing a multiplicative separability assumption on the distance functions, they are able to decompose the Malmquist productivity change index into three components, namely quality change, technical change and efficiency change.

Another application of the same idea, i.e., of decomposing economic indexes into various components, is the paper by Jaenicke and Lengnick (1999). Merging the soil science literature on soil-quality indexes with the literature on efficiency and total factor productivity indexes, they isolate a theoretically preferred soil-quality index. In addition, using common regression techniques they shed light on the role of individual soil quality properties in a linear approximation of the estimated soil-quality index.

A different but somewhat related strand of the literature deals with the environmental impacts in the measurement of efficiency and productivity growth. Färe *et al.* (1989) indeed started what has become now a relatively vast literature extending efficiency measurement when some outputs are undesirable. [9] The central notion of this paper, and of many that followed (for a recent application and partial survey see Ball *et al.*, 2001), is that of weak disposability of outputs. To credit firms or industries for their effort to cut off on pollutants, technology is modeled so that it can handle the case when the reduction of some (bad) outputs requires the reduction of some of the other outputs and/or the increase of inputs.

Besides the concept of output weak disposability, an interesting and useful idea for our setting is the directional distance function, a generalization of the radial distance function introduced to production economics by Chambers, Chung and Färe (1996) who extended and adapted the idea of the translation functions of Kolm (1976) and Blackorby and Donaldson (1980), and of the benefit function introduced in consumer theory by Luenberger (1992, 1994). The directional distance function allows to compare different firms and to measure their distance from the frontier of the technology moving along a preassigned direction. In this fashion it is possible to evaluate the performance of the firms that need to increase the production of the good outputs and decrease that of bad outputs (Chung, Färe and Grosskopf, 1999).

The first attempt to use the directional distance function to take into account the quality of outputs in a different context, i.e., health services, is a paper by Dismuke and Sena (2001). They consider the mortality rate as a (bad) quality

[9] The first contribution that takes into account bad outputs is probably the work of Pittman (1983), who extends the approach of CCD, specifies a modified Tornqvist output index and uses dual data on pollutants' shadow prices to adjust the revenue shares.

attribute of the hospital production process and use directional distance functions to calculate a Luenberger-Malmquist productivity index. They are then able to decompose the productivity index into a quality index, plus a technical change and efficiency change components.

In this paper we use the idea of the directional distance function to incorporate quality attributes into the technology, but we depart from the models reviewed above in the construction of an indicator instead of an index. In fact, following Chambers (1998 and 2002), we use the directional distance function to construct an indicator, that is an output aggregator that is expressed in difference forms rather than in ratio forms like in the case of the more traditional Malmquist productivity index. This difference stems from the property of the directional distance functions, which make the Luenberger indicator translation invariant in outputs, to contrast with the property of homogeneity of degree zero in outputs of the Malmquist index coming from the linear homogeneity of the output distance function *à la* Shephard (1970).

We propose an indicator based on directional distance functions for different reasons. First, as explained above, we compare firms based on the distance from the frontier along a preassigned direction which reflects the preference and needs of the buyer or downstream firm with respect to the quality attributes. Second, it may be the case that to be valuable to a downstream firm, the composition of the raw material has to be close to an "ideal" bundle of attributes preferred by the buyer. In other words, in some instances the composition has to be well balanced and some of the attributes have to be within a certain range.[10] The choice of the direction allows then to take this into account and evaluate the quality attributes produced by a pool of suppliers according to buyers' needs.

3. Notation and model specification

Let $\mathbf{x} \in \Re^N_+$ be a vector of inputs, $y \in \Re_+$ the output level, i.e., the yield, and $\mathbf{s} \in \Re^M_+$ a vector of quality attributes. We treat attributes as outputs, and we can

[10] In the paper we refer to quality attributes. In the literature, quality is usually associated with vertical differentiation, that is the situation in which, given the same price for the good, all consumers unambiguosly prefer more to less of a certain attribute. The other case is that of horizontal differentiation, in which case there is not such a unique ordering among consumers (see, e.g., Tirole, 1988). In our paper we use quality generically, but according to the above definition it would be more appropriate to call it quality only when it is always better for the buyer to have more of the attributes. Accordingly, it would be inappropriate to use it when there is a need for a well balanced composition of the raw commodity.

think of the vector $(y, \mathbf{s})$ as the output vector.[11] The technology can be defined in terms of a set $T \subset \Re_{+}^{N} \times \Re_{+} \times \Re_{+}^{M}$

$$T = \left\{ (\mathbf{x} \in \Re_{+}^{N}, \quad y \in \Re_{+} \quad \mathbf{s} \in \Re_{+}^{M}) : \mathbf{x} \text{ can produce } (y, \mathbf{s}) \right\}.$$

In words, the technology consists of all output and attributes that are feasible for some input vector. T satisfies the following properties (Chambers, 2002):

T.1: T is closed;

T.2: Inputs and outputs are freely disposable, i.e., if $(\mathbf{x}',-y', -\mathbf{s}') \geq (\mathbf{x},-y, -\mathbf{s})$ then $(\mathbf{x},y, \mathbf{s}) \in T \Rightarrow (\mathbf{x}', y', \mathbf{s}') \in T$;

T.3: Doing nothing is feasible, i.e., $(0^n, 0, 0^m) \in T$.

Related to T are the input set, $V(y, \mathbf{s}) = \{\mathbf{x} : (\mathbf{x}, y, \mathbf{s}) \in T\}$, and the output set, $Y(\mathbf{x}) = \{(y, \mathbf{s}) : (\mathbf{x}, y, \mathbf{s}) \in T\}$.

Following Chambers, Chung, and Färe (1996, 1998), and Chambers (2002), we can define the *directional technology distance function* as:

$$\begin{aligned} \overrightarrow{D}_T(\mathbf{x},y, \mathbf{s}; \mathbf{g_x}, g_y, \mathbf{g_s}) &= \max\{\beta \in \Re : (\mathbf{x} - \beta \mathbf{g_x},\ y + \beta g_y,\ \mathbf{s} + \beta \mathbf{g_s}) \in T\}, \\ \mathbf{g_x} &\in \Re_{+}^{N},\ g_y \in \Re_{+},\ \mathbf{g_s} \in \Re_{+}^{M},\ (\mathbf{g_x}, g_y, \mathbf{g_s}) \neq (\mathbf{0}^N, 0, \mathbf{0}^M), \end{aligned}$$

if $(\mathbf{x} - \beta \mathbf{g_x},\ y + \beta g_y,\ \mathbf{s} + \beta \mathbf{g_s}) \in T$ for some β and $dT(y, \mathbf{s},g_y, \mathbf{g_s})$ =inf$\{\delta \in \Re : (y{+}\delta g_y \in \Re_{+},\ \mathbf{s}{+}\delta \mathbf{g_s} \in \Re_{+}^{M})\}$ otherwise. Note that $(\mathbf{g_x}, g_y, \mathbf{g_s})$ is a reference vector of inputs and outputs which determines the direction over which the distance function is determined. $\overrightarrow{D}_T(\mathbf{x}, \mathbf{y}; \mathbf{g_x}, g_y, \mathbf{g_s})$ represents the maximal translation of the input and output vector in the direction of $(\mathbf{g_x}, g_y, \mathbf{g_s})$ that keeps the translated input and output vector inside T.

The properties of the directional distance function are the following (Luenberger 1992, 1994, 1995; Chambers, Chung, and Färe 1995, 1996):

1. $\overrightarrow{D}_T(\mathbf{x} - \boldsymbol{\alpha} \mathbf{g_x}, y + \alpha g_y,\ \mathbf{s} + \alpha \mathbf{g_s}; \mathbf{g_x}, g_y, \mathbf{g_s}) = \overrightarrow{D}_T(\mathbf{x},y, \mathbf{s}; \mathbf{g_x}, g_y, \mathbf{g_s}) - \alpha$;
2. $\overrightarrow{D}_T(\mathbf{x},y, \mathbf{s}; \mathbf{g_x}, g_y, \mathbf{g_s})$ is upper semi-continuous in x and y jointly;
3. $\overrightarrow{D}_T(\mathbf{x},y, \mathbf{s}; \lambda \mathbf{g_x}, \lambda g_y, \mathbf{g_s}) = \frac{1}{\lambda} \overrightarrow{D}_T(\mathbf{x}, \mathbf{y}; \mathbf{g_x}, g_y, \mathbf{g_s})$, $\lambda > 0$;
4. $(y' \geq y,\ \mathbf{s}' \geq \mathbf{s}) \Longrightarrow \overrightarrow{D}_T(\mathbf{x},y', \mathbf{s}'; \mathbf{g_x}, g_y, \mathbf{g_s}) \leq \overrightarrow{D}_T(\mathbf{x},y, \mathbf{s}; \mathbf{g_x}, g_y, \mathbf{g_s})$;
5. $\mathbf{x}' \geq \mathbf{x} \Longrightarrow \overrightarrow{D}_T(\mathbf{x}',y, \mathbf{s}; \mathbf{g_x}, g_y, \mathbf{g_s}) \geq \overrightarrow{D}_T(\mathbf{x},y, \mathbf{s}; \mathbf{g_x}, g_y, \mathbf{g_s})$;
6. if T is convex, $\overrightarrow{D}_T(\mathbf{x},y, \mathbf{s}; \mathbf{g_x}, g_y, \mathbf{g_s})$ is concave in (x, y, s).

[11] In the following of the text, we use interchangeably yields, production level, or output to mean the scalar y, while we use quality attributes to refer to $\mathbf{s}$. When we use outputs we refer instead to the output vector $(y, \mathbf{s})$.

As shown by Chambers, Chung, and Färe (1996), all known (radial) distance and directional distance functions can be depicted as special cases of the directional technology distance function. One example, which will be used in this paper, is the *directional output distance function* (Chambers, Chung, and Färe 1998), which can be defined as:

$$\begin{aligned} \overrightarrow{D}_O(\mathbf{x}, y, \mathbf{s}; \mathbf{0}^N, g_y, \mathbf{g_s}) &= \max\{\beta \in \Re : (\mathbf{x},\ y + \beta g_y,\ \mathbf{s}+\beta \mathbf{g_s}) \in T\}, \quad (3.1) \\ g_y &\in \Re_+,\ g_y \neq 0,\ \mathbf{g_s} \in \Re^M_+,\ \mathbf{g_s} \neq \mathbf{0}^M, \end{aligned}$$

if $(\mathbf{x},\ y + \beta g_y,\ \mathbf{s}+\beta \mathbf{g_s}) \in T$ for some β and $+\infty$ otherwise. $\overrightarrow{D}_O(\mathbf{x}, y, \mathbf{s}; \mathbf{0}^N, g_y, \mathbf{g_s})$ represents the maximal translation of the output vector in the direction of $(g_y, \mathbf{g_s})$ that keeps the translated output vector inside T. Notice that under the assumption of output free disposability, the directional output distance function is a complete representation of the technology (Chambers, Chung, and Färe 1998):

$$\overrightarrow{D}_O(\mathbf{x}, y, \mathbf{s}; \mathbf{0}, g_y, \mathbf{g_s}) \leq 0 \qquad \Leftrightarrow \qquad (y, \mathbf{s}) \in Y(\mathbf{x}).$$

If we assume instead weak disposability of outputs, the directional output distance function can be a proper representation of technology only with an appropriate choice of g. Indeed, when $g_y = y$ and $\mathbf{g_s} = \mathbf{s}$, then we can always recover the output set $Y(\mathbf{x})$ from $\overrightarrow{D}_O(\mathbf{x}, y, \mathbf{s}; \mathbf{0}, y, \mathbf{s})$ (see Chambers, Chung and Färe, 1996, for a proof in the case of the directional input distance function).

3.1. The Luenberger Quality Indicator

In this paper we are interested in constructing an index - more precisely, an indicator in the case of the directional distance function - of quality attributes of the output. The general purpose of an index is that it can create a summary measure of inputs or outputs that can be used to evaluate how these aggregate quantities vary across firms (or time). For our purposes, we start from the directional output distance function, and we change notation to accommodate for the quality attributes of the intermediate product, i.e., sugar content, pH, etc. We can then write the *directional quality distance function* with the following:

$$\begin{aligned} \overrightarrow{D}_Q(\mathbf{x}, y, \mathbf{s}; \mathbf{0}^N, 0, \mathbf{g_s}) &= \max\{\beta \in \Re : (\mathbf{x},\ y, \mathbf{s} + \beta \mathbf{g_s}) \in T\}, \quad (3.2) \\ \mathbf{g_s} &\in \Re^M_+,\ \mathbf{g_s} \neq \mathbf{0}^M. \end{aligned}$$

Notice that this quality distance function is a modified version of the directional output distance function: in this latter, the production level y is expanded as well, while in the former only the quality attributes vector is expanded. As a matter of comparison, it is useful to compare the directional quality distance function with the Shephard (radial) quality distance function, which is defined as the following

$$D_Q(\mathbf{x}, y, \mathbf{s}) = \inf_{\theta}\{\theta > 0 : (\mathbf{x}, y, \frac{\mathbf{s}}{\theta}) \in T\},$$

and represents the minimum (technically, the infimum) that the quality bundle can be expanded and still be feasible. Again, this is a modified version of the radial output distance function, in which also the production level y is expanded. It is worth reminding the reader that the Shephard distance function is related to the directional quality distance function when $\mathbf{g_s} = \mathbf{s}$, i.e., when the direction is given by the firms' choices of quality attributes, by the following (see, e.g., Chambers, Chung, and Färe 1998: 355, for the directional output distance functions):

$$\overrightarrow{D}_Q(\mathbf{x}, y, \mathbf{s}; \mathbf{0}^N, 0, \mathbf{s}) = \frac{1}{D_Q(\mathbf{x}, y, \mathbf{s})} - 1. \tag{3.3}$$

The basic idea of the quality indicator is to have a summary measure of quality attributes that may be used to see how these qualities vary over space (or over time for that matter). For our purposes, we need to compare input/output/attributes combinations of different suppliers, i.e., firms. Let us suppose we want to compare a firm $i = 1$ to a reference firm $i = 0$. Adapting the indicators suggested by Chambers (2002), we can define the *1-technology Luenberger quality indicator* for $(\mathbf{x}^1, y^1, \mathbf{s}^1, \mathbf{s}^0)$ by the following:

$$Q^1(\mathbf{s}^0, \mathbf{s}^1, y^1, \mathbf{x}^1) = \overrightarrow{D}^1_Q(\mathbf{x}^1, y^1, \mathbf{s}^0; \mathbf{0}^N, 0, \mathbf{g_s}) - \overrightarrow{D}^1_Q(\mathbf{x}^1, y^1, \mathbf{s}^1; \mathbf{0}^N, 0, \mathbf{g_s}). \tag{3.4}$$

$Q^1(\mathbf{s}^0, \mathbf{s}^1, y^1, \mathbf{x}^1)$ represents the difference between the amount that it is possible to translate $\mathbf{s}^0$ and $\mathbf{s}^1$ into the direction $\mathbf{g_s}$ and still keep both quality bundles in the output set of firm 1, i.e., we are referring to firm's 1 technology or input-output bundle $(\mathbf{x}^1, y^1)$. We can illustrate the indicator with a graphical representation. In figure 1, in the attributes' space we represent two quality output sets, $S(\mathbf{x}^1, y^1)$ and $S(\mathbf{x}^0, y^0)$,[12] consistent with $(\mathbf{x}^1, y^1)$ and $(\mathbf{x}^0, y^0)$ respectively, that is the input vector/output level of the observation under consideration and of the reference firm, respectively. We also represent firm 1's quality bundle, $\mathbf{s}^1$, with its two quality components, i.e., s^1_1 and s^1_0, together with the base $\mathbf{s}^0$ and its two quality components, s^0_1 and s^0_0. For exposition simplicity, for the direction we use a simple

[12] We can define the quality output set as the following $S(\mathbf{x}, \mathbf{y}) = \{\mathbf{s} : (\mathbf{x}, y, \mathbf{s}) \in T\}$.

reference vector, and we set it equal to the unitary vector, i.e., $\mathbf{g_s} = 1, 1$. Now consider $\overrightarrow{D}^1_Q(\mathbf{x}^1,y^1,\mathbf{s}^0;\mathbf{0}^N,0,\mathbf{g_s})$: it is the distance from $\mathbf{s}^0$ to the outer contour of $S(\mathbf{x}^1, y^1)$, moving in the direction parallel to the bisector, since $\mathbf{g_s} = 1, 1$. Similarly, $\overrightarrow{D}^1_Q(\mathbf{x}^1,y^1,\mathbf{s}^1;\mathbf{0}^N,0,\mathbf{g_s})$ is the distance from $\mathbf{s}^1$, in the same direction, to the outer contour of $S(\mathbf{x}^1, y^1)$. Given the picture, relative to the output set of firm 1, $S(\mathbf{x}^1, y^1)$, the distance of firm 1 is lower and hence firm 1 has higher quality than the reference firm 0.

[Insert Figure 1 about here]

Looking at it in another fashion, $\overrightarrow{D}^1_Q(\mathbf{x}^1,y^1,\mathbf{s}^0;\mathbf{0}^N,0,\mathbf{g_s})$ may be seen as representing the number of units of the reference vector, $\mathbf{g_s}$, that can be added to $\mathbf{s}^0$ while using the input-output bundle for firm 1, $(\mathbf{x}^1,y^1)$. It can be a positive number, meaning that the input-output bundle of firm 1 is consistent with a "higher" quality level than that of firm 0. Or it can be a negative number, in which case it is consistent with a "lower" quality level. So if $Q^1(\mathbf{s}^0, \mathbf{s}^1, y^1, \mathbf{x}^1) > 0$ we can conclude that quality is higher for firm 1 than for firm 0 from the input-output perspective of firm 1, i.e., using firm's 1 technology, since we consider $(y^1, \mathbf{x}^1)$.

The *0-technology Luenberger quality indicator* for $(\mathbf{x}^0, y^0, \mathbf{s}^1, \mathbf{s}^0)$ is defined by the following:

$$Q^0(\mathbf{s}^0, \mathbf{s}^1, y^0, \mathbf{x}^0) = \overrightarrow{D}^0_Q(\mathbf{x}^0,y^0,\mathbf{s}^0;\mathbf{0}^N,0,\mathbf{g_s}) - \overrightarrow{D}^0_Q(\mathbf{x}^0,y^0,\mathbf{s}^1;\mathbf{0}^N,0,\mathbf{g_s}). \tag{3.5}$$

Note that in this case we are computing the indicator from a different basis of comparison, i.e., from firm 0's perspective, since we consider its input-output bundle $(\mathbf{x}^0,y^0)$. If $Q^0(\mathbf{s}^0, \mathbf{s}^1, y^0, \mathbf{x}^0) > 0$, the quality is higher for firm 1 than firm 0, using as a reference firm 0's technology or input-output bundle $(\mathbf{x}^0, y^0)$.

As it is the case with the more common Malmquist index, the choice of the technology to use as a comparison can affect the results. In other words, it may happen that a firm results more productive when compared to a technology and less when compared to another technology. For instance, in figure 1 firm 1 results more productive with the quality indicator referring to firm's 1 technology, and less productive when referring to the firm's 0 technology. It would be better to have an indicator that is invariant to the technology chosen to make the comparison. A natural compromise then is to take the average of these two indicators (Chambers, 1998). Thus the *Luenberger quality indicator* is the average of $Q^1(\mathbf{s}^0, \mathbf{s}^1, y^1, \mathbf{x}^1)$ and $Q^0(\mathbf{s}^0, \mathbf{s}^1, y^0, \mathbf{x}^0)$:

$$Q(\mathbf{s}^0, \mathbf{s}^1, y^0, y^1, \mathbf{x}^0, \mathbf{x}^1) = \frac{1}{2}\left(Q^1(\mathbf{s}^0, \mathbf{s}^1, y^1, \mathbf{x}^1) + Q^0(\mathbf{s}^0, \mathbf{s}^1, y^0, \mathbf{x}^0)\right). \tag{3.6}$$

Given figure 1, relative to the quality set of firm 0, $S(\mathbf{x}^0,y^0)$, the distance of firm 0 is lower and hence firm 0 has higher quality than the other firm 1. Referring to the technology $S(\mathbf{x}^1,y^1)$,[13] s^1 is closer to the frontier than s^0. Taking the average of the two differences in the distances calculated gives the Luenberger quality indicator in eq. (3.6).

For comparison purposes, we would like to relate these results to those obtainable using a more common methodology. For this purpose we employ a Malmquist index (Färe, Grosskopf and Roos, 1995) modified to take into account for quality attributes, and which becomes the following:

$$M(\mathbf{s}^0, \mathbf{s}^1, y^0, y^1, \mathbf{x}^0, \mathbf{x}^1) = \left[\frac{D_O^1(s^0, x^1, y^1)}{D_O^1(s^1, x^1, y^1)} \frac{D_O^0(s^0, x^0, y^0)}{D_O^0(s^1, x^0, y^0)} \right]^{\frac{1}{2}}. \qquad (3.7)$$

While the Luenberger indicator is the average expressed in difference form, the Malmquist quality index is the geometric mean of the ratio of comparisons of different quality attributes levels attainable with different input-output bundles. The first ratio in the brackets, indeed, compares the quality attributes of firm 1 to those of the reference firm in terms of firm's 1 technology, i.e., using $(\mathbf{x}^1, y^1)$. The second ratio, on the other hand, compares the two observations using firm's 0 technology. Notice also that by taking the natural logarithm of eq. (3.7) we obtain something similar to eq. (3.6). The two are actually equivalent when $\mathbf{g_s} = \mathbf{s}$.

The main difference between the two measures, the Malmquist and the Luenberger, based on their respective distance function, is the fact that the direction is chosen by the researcher and equal for all firms in the case of the directional distance function. In the case of the radial distance function, the direction is not given and may be different among all firms. In fact, the direction is that from the observation to the frontier along the ray emanating from the origin. In figure 1, for firm 1, the radial distance is represented with the broken line continuing the ray emanating from the origin and going through s^1.

4. Activity analysis and empirical implementation

For the estimation of the production technology, parametric and non-parametric methodologies are available. Among these latter, Data Envelopment Analysis (DEA) employs linear programming to construct a piecewise linear representation

[13] See the broken lines in figure 1, refering to the distance from the technology of firm 0, $S(\mathbf{x}^0,y^0)$, to be compared with the solid lines referring to $S(\mathbf{x}^1,y^1)$.

of the frontier technology.[14] DEA constructs a convex hull around the observed inputs and outputs of the firms in the sample. In the output space, for instance, DEA traces the transformation curve of the outputs that can be produced with a certain level of inputs. With DEA, the inputs-outputs observed in a sample can then be used to measure the distance of each observation from the frontier, and the distance function measures are then employed for the calculation of productivity indexes, like the quality productivity indexes or indicators proposed in this study.

Although no specific functional forms are assumed in DEA, the shape of the production frontier is influenced by the assumptions regarding the returns to scale and the disposability of inputs and outputs. Constant returns to scale (CRS) means that an increase in inputs leads to a proportional increase in the outputs. On the other hand, variable returns to scale (VRS) implies that an increase of the inputs leads to a non proportional increase in outputs, with an initial tract in which returns are increasing and then with decreasing returns. As other possibilities, the technology could have non-decreasing returns (NDRS) or non-increasing returns (NIRS).

Using the techniques of activity analysis, various technologies can be constructed from the K observed, feasible activities. For instance, the technology associated with a cross-section sample of firms, under constant returns to scale (C), strong disposability of inputs (S), output (S) and quality attributes (S) respectively, is the following (modified from Färe, Grosskopf and Lovell, 1994)

$$T = \Bigg\{ (\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}) : \sum_{k=1}^{K} z_k y_k \geq y_{k'},$$

$$\begin{aligned} \sum_{k=1}^{K} z_k s_{km} &\geq s_{k'm},\ m = 1, ..., M, \\ \sum_{k=1}^{K} z_k x_{kn} &\leq x_{k'n},\ n = 1, ..., N, \\ & z_k \geq 0,\ k = 1, ..., K \} , \end{aligned} \tag{4.1}$$

where we have K observations of inputs, output level and quality attributes, i.e., $(\mathbf{x}^k, y^k, \mathbf{s}^k)$, with $k = 1, ..., K$ firms. Notice that, regarding returns to scale, $z_k \geq 0$

[14]DEA is deterministic and does not impose any functional form on the technology. For a comparison of strenghts and weaknesses of different methods the reader can refer to Lovell (1993) and Murillo-Zamorano (2004).

in the last constraint imposes CRS. To have a technology with variable returns to scale, one needs to change the last constraint to $\sum_{k=1}^{K} z_k = 1$. For a technology with NDRS, the last constraint above would need to be changed to $\sum_{k=1}^{K} z_k \geq 1$, while a NIRS technology would be characterized by $\sum_{k=1}^{K} z_k \leq 1$ (Färe, Grosskopf and Lovell, 1994: 50)

DEA allows also to evaluate the distance of each firm in the sample from the best practice frontier. The distance from different specifications of the technology represents a measure of the technical efficiency of production units[15] and forms the basis for the construction of the quality indicators proposed in this study. Referring to a technology with variable returns to scale (VRS), the linear program problem to solve in order to compute the **directional output distance function** in eq. (3.1), for each observation k', is the following (Chambers, Färe and Grosskopf, 1996)

$$\overrightarrow{D}_O(\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}; \mathbf{0}^N, g_y, \mathbf{g_s}) = \max\ \beta :$$

$$\begin{aligned} \sum_{k=1}^{K} z_k y_k &\geq y_{k'} + \beta g_y, \\ \sum_{k=1}^{K} z_k s_{km} &\geq s_{k'm} + \beta \mathbf{g_s},\ m = 1, ..., M, \\ \sum_{k=1}^{K} z_k x_{kn} &\leq x_{k'n},\ n = 1, ..., N, \\ \sum_{k=1}^{K} z_k &= 1,\ k = 1, ..., K, \end{aligned} \tag{4.2}$$

where g_y and $\mathbf{g_s}$ are the direction vectors for output and quality attributes respectively. In this study we will consider different direction vectors for g_y and $\mathbf{g_s}$, but a benchmark direction is given by $g_y = y_{k'}$ and $\mathbf{g_s} = \mathbf{s}_{k'm}$, i.e., in the direction of the observation. In this case, the linear programme to solve for the directional output distance function, in case of CRS, is the following

$$\overrightarrow{D}_O(\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}; \mathbf{0}^N, y_{k'}, \mathbf{s}_{k'm}) = \max\ \beta :$$

[15] The radial distance functions *à la* Shephard is related to the technical efficiency *à la* Farrell by the following: $\theta = \frac{1}{D_O(\mathbf{x}, y, \mathbf{s})}$, where θ is the Farrell technical efficiency and $D_O(\mathbf{x}, y, \mathbf{s})$ is the radial Shephard measure defined in the text (see, e.g., Färe and Primont, 1995).

$$\begin{aligned}\sum_{k=1}^{K} z_k y_k &\geq y_{k'}(1+\beta), \\ \sum_{k=1}^{K} z_k s_{km} &\geq s_{k'm}(1+\beta),\ m=1,...,M, \\ \sum_{k=1}^{K} z_k x_{kn} &\leq x_{k'n},\ n=1,...,N, \\ z_k &\geq 0,\ k=1,...,K,\end{aligned} \tag{4.3}$$

To investigate whether there are significant differences between the different returns to scale or, more generally, between different specifications of technology or quality indicators, we proceed along two different venues. First, following the arguments put forth by Banker (1996) for the cases in which no particular assumptions can be made regarding the distribution of the measures to be investigated, such as our directional efficiency measures or the indicators based on it, we employ a distribution-free statistic based on the Kolmogorov Smirnov test, like the following:

$$t_{KS} = \max\left\{F_V(I^j) - F_C(I^j)\right\}, \qquad for \quad j = 1,..,K,$$

where $F_V(I^j)$ and $F_C(I^j)$ are the empirical distributions, respectively for a variable (V) or constant (C) returns to scale specification of the technology, and I^j are the calculated distance from the specified technology. Second, we employ another test, the Mann-Whithney test, that also allows to establish on whether two samples are from the same distribution. Both methodologies, called KS and MW respectively in the text, are used to test the null that the two distributions, i.e., specifications, are the same against the alternative hypothesis that they are different.

4.1. The disposability properties of the technology

In our explorative study of the technology, we look at the output disposability properties of the sample of observations under consideration. While we do not have a priory reasons to expect congestion on the input side, i.e., no need to test for input weak disposability, on the output side we decide to test whether the technology presents either strong or weak output (or quality attributes) disposability. Strong disposability of outputs (SDO) assumes that it is possible to reduce each output (or quality attribute, in this study) individually without the need to reduce the other outputs or increase the use of inputs. This implies that the outputs are "goods", i.e., with a non negative marginal costs, and that outputs are substitutes. Weak disposability of outputs (WDO), on the other hand, means that in order to reduce one output it is necessary to reduce other outputs as well (or to increase inputs). This case is relevant, for instance, when one output is pollution and the other is a good, or when outputs are complements. This latter aspect is more relevant for our study, since we want to characterize the relationships among different outputs in the production process.

For instance, consider two quality attributes, s_1 and s_2. If we represent their relationship with the output set, i.e., the collection of output vectors that are obtainable from the input vector, we can have different situations (figure 2). For instance, the tract 0ABCD represents the frontier of a strongly disposable technology, and s_1 and s_2 are strongly disposable or substitutes in the production process. On the other hand, 0EBCD represents a weakly disposable technology, in which the output s_1 is weakly disposable, i.e., it is the congesting or complementary output. It may happen that some of the outputs are strongly disposable, while others are weakly disposable.

[Insert Figure 2 about here]

On the input side, strong disposability of inputs (SDI) assumes that all the inputs can be increased without reducing the outputs, i.e., there is no congestion, and the marginal product of inputs is non-negative. The alternative would be weak disposability of inputs (WDI), when increasing one input needs to be accompanied by an increase in the same proportion of all the other inputs to keep the same output level, i.e., there is congestion. In this study we concentrate on the output side and thus we just assume SDI.

To characterize the output disposability properties of the technology for our observations, we pursue an investigative strategy in different stages. First, we test A) whether jointly all outputs, that is production level (yields) and quality attributes, are weakly disposable (H_1: W) against the null that they are all strongly disposable (H_0: S). To do so, we compare the distribution of the directional output distance measures computed with eq.(4.3) to those computed with weak disposability of outputs via a linear programme like the following[16]

$$\overrightarrow{D}_O(\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}; \mathbf{0}^N, y_{k'}, \mathbf{s}_{k'm}) = \max\ \beta :$$

[16] Notice that when testing for Returns to Scale and disposability properties, we choose $\mathbf{g}_\mathbf{s} = \mathbf{s}_{k'}$ and $g_y = y_{k'}$ for the direction vector.

$$\sum_{k=1}^{K} z_k y_k = y_{k'}(1+\beta), \tag{4.4}$$
$$\sum_{k=1}^{K} z_k s_{km} = s_{k'm}(1+\beta),\ m = 1, ..., M,$$
$$\sum_{k=1}^{K} z_k x_{kn} \leq x_{k'n},\ n = 1, ..., N,$$
$$z_k \geq 0,\ k = 1, ..., K,$$

by doing the relative statistical tests of KS and MW. Notice that in this linear programing formulation, the equality sign (=) in the first and second constraint imposes WDO on the technology (Chambers, Färe, and Grosskopf, 1996). In an analogous manner, the inequality sign ($\leq$) in the third constraint imposes SDI, while an equality constraint would impose WDI.[17]

To explore further the disposability properties of each output, i.e., yields and quality attributes, taken individually, we test B) whether each of them is weakly disposable (H_1: W^i) against the null that they are all jointly strongly disposable (H_0: S). For instance, to test whether the output level, i.e., the yields, is weakly disposable, we calculate the alternative (H_1) in which only the yields are WDO by computing the following

$$\overrightarrow{D}_O(\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}; \mathbf{0}^N, y_{k'}, \mathbf{s}_{k'm}) = \max\ \beta :$$

$$\sum_{k=1}^{K} z_k y_k = y_{k'}(1+\beta), \tag{4.5}$$
$$\sum_{k=1}^{K} z_k s_{km} \geq s_{k'm}(1+\beta),\ m = 1, ..., M,$$
$$\sum_{k=1}^{K} z_k x_{kn} \leq x_{k'n},\ n = 1, ..., N,$$
$$z_k \geq 0,\ k = 1, ..., K,$$

[17] Notice also that we compute the distance imposing CRS, when usually the disposability tests are performed using a VRS technology (see, e.g., Färe *et al.*, 1994). As will be presented in the text, however, our data show that the true technology is CRS and no detectable differences emerge between the two different scale specifications of the technology. We thus believe that imposing the CRS specification gives the same results and it is innocuous for our purposes.

and we test it against the null (H_0) of all outputs being SDO computed via eq. (4.3).

To investigate further the relationships of each individual quality attribute with the production level, for each quality attribute we check C) whether

i) the quality attribute is weakly disposable with the output level, and the output level is weakly disposable with the quality attribute as well;

ii) the quality attribute is weakly disposable with the output level, but the output level is strongly disposable with the quality attribute;

iii) the quality attribute is strongly disposable with the output level, but the output level is weakly disposable with the quality attribute;

iv) neither the quality attribute is weakly disposable with the output level, nor the output level is weakly disposable with the quality attribute.

To ascertain which is the true among these four different cases, we construct the tests in the following fashion. First, we look at the disposability properties of the output level with regard to the quality attribute by looking at the H_1 that both yields and the quality attribute are weakly disposable (H_1: $W^{s_i y}$) by computing the following

$$\overrightarrow{D}_O(\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}; \mathbf{0}^N, y_{k'}, \mathbf{s}_{k'm}) = \max\ \beta :$$

$$\begin{aligned}
\sum_{k=1}^{K} z_k y_k &= y_{k'}(1+\beta), \qquad (4.6)\\
\sum_{k=1}^{K} z_k s_{k1} &= s_{k'1}(1+\beta),\\
\sum_{k=1}^{K} z_k s_{km} &\geq s_{k'm}(1+\beta),\ m = 2, ..., M,\\
\sum_{k=1}^{K} z_k x_{kn} &\leq x_{k'n},\ n = 1, ..., N,\\
z_k &\geq 0,\ k = 1, ..., K,
\end{aligned}$$

where, for instance, for the quality attribute we consider sugar (s_1), and we test it against the null that only sugar is weakly disposable (H_0: W^{s_i}), that is by computing the following

$$\overrightarrow{D}_O(\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}; \mathbf{0}^N, y_{k'}, \mathbf{s}_{k'm}) = \max\ \beta :$$

$$\begin{aligned}
\sum_{k=1}^{K} z_k y_k &\leq y_{k'}(1+\beta), \qquad (4.7)\\
\sum_{k=1}^{K} z_k s_{k1} &= s_{k'1}(1+\beta),\\
\sum_{k=1}^{K} z_k s_{km} &\geq s_{k'm}(1+\beta),\ m=2,...,M,\\
\sum_{k=1}^{K} z_k x_{kn} &\leq x_{k'n},\ n=1,...,N,\\
z_k &\geq 0,\ k=1,...,K.
\end{aligned}$$

Second, we now look at the H_1 that both yields and the quality attribute are weakly disposable (H_1: $W^{s_i y}$) by computing eq. (4.6) against the null that only the output level is weakly disposable (eq. 4.5). The distributions computed with eq. (4.6) and (4.5) can be either different (call it case a) or the same (case b). In an analogous manner, those computed via eq. (4.6) and (4.7) are different (case c) or the same (case d). Thus, there can be four possibilities, combining cases a/b with cases c/d.

When a and c occur together, we have that the quality attribute and the output level are both weak disposable. In other words, they are complement in production (this corresponds to the case i) above). With a and d, the quality attribute is weakly disposable, i.e., complement, with the output level, but not the other way around (case ii). The opposite would be with b and c, when the yields would be a complement with the quality attribute but not vice-versa (case iii). The last possibility, with b and d, is when both the quality attribute and the output level are substitute of each other (case iv).

4.2. The quality indicators

To compute the quality indicator proposed in eq. (3.6), we need to use and compute four different quality directional distance functions of the type of eq. (3.2). For instance, to compute $\overrightarrow{D}_Q^1(\mathbf{x}^1, y^1, \mathbf{s}^1; \mathbf{0}^N, 0, \mathbf{g_s})$ of eq. (3.4), that is the directional quality distance function of the observation under consideration k' referring to its own input-output bundle, we need to solve the following

$$\overrightarrow{D}_Q^1(\mathbf{x}_{k'}^1, y_{k'}^1, \mathbf{s}_{k'}^1; \mathbf{0}^N, 0, \mathbf{g_s}) = \max\ \beta :$$

$$\begin{aligned}
\sum_{k=1}^{K} z_k y_k^1 &\geq y_{k'}^1, \\
\sum_{k=1}^{K} z_k s_{km}^1 &\geq s_{k'm}^1 + \beta \mathbf{g_s},\ m = 1, ..., M, \\
\sum_{k=1}^{K} z_k x_{kn}^1 &\leq x_{k'n}^1,\ n = 1, ..., N, \\
z_k &\geq 0,\ k = 1, ..., K,
\end{aligned} \tag{4.8}$$

where the superscript 1 refers to the fact that we use the inputs-output bundle of the firms under examination, $(\mathbf{x}^1, y^1)$. In the case of $\overrightarrow{D}_Q^1(\mathbf{x}^1, y^1, \mathbf{s}^0; \mathbf{0}^N, 0, \mathbf{g_s})$, we change the second constraint to $\sum_{k=1}^{K} z_k s_{km}^1 \geq s_{k'm}^0 + \beta \mathbf{g_s}$, since we are now referring to the quality attributes bundle of the base, $(\mathbf{s}^0)$, but still using the observations' own input-output bundle, to have

$$\overrightarrow{D}_Q^1(\mathbf{x}_{k'}^1, y_{k'}^1, \mathbf{s}_{k'}^0; \mathbf{0}^N, 0, \mathbf{g_s}) = \max\ \beta :$$

$$\begin{aligned}
\sum_{k=1}^{K} z_k y_k^1 &\geq y_{k'}^1, \\
\sum_{k=1}^{K} z_k s_{km}^1 &\geq s_{k'm}^0 + \beta \mathbf{g_s},\ m = 1, ..., M, \\
\sum_{k=1}^{K} z_k x_{kn}^1 &\leq x_{k'n}^1,\ n = 1, ..., N, \\
z_k &\geq 0,\ k = 1, ..., K,
\end{aligned} \tag{4.9}$$

On the other hand, in the case of $\overrightarrow{D}_Q^0(\mathbf{x}_{k'}^0, y_{k'}^0, \mathbf{s}_{k'}^1; \mathbf{0}^N, 0, \mathbf{g_s})$, we need to compare the quality attributes of each observation to the input vector and quantity level of the base or "average firm", $(\mathbf{x}^0, y^0)$. In this case we solve the following

$$\overrightarrow{D}_Q^0(\mathbf{x}_{k'}^0, y_{k'}^0, \mathbf{s}_{k'}^1; \mathbf{0}^N, 0, \mathbf{g_s}) = \max\ \beta :$$

$$
\begin{aligned}
\sum_{k=1}^{K} z_k y_k^1 &\geq y_{k'}^0, \qquad (4.10)\\
\sum_{k=1}^{K} z_k s_{km}^1 &\geq s_{k'm}^1 + \beta \mathbf{g_s},\ m = 1, ..., M,\\
\sum_{k=1}^{K} z_k x_{kn}^1 &\leq x_{k'n}^0,\ n = 1, ..., N,\\
z_k &\geq 0,\ k = 1, ..., K.
\end{aligned}
$$

Last, in the case of $\overrightarrow{D}_Q^0(\mathbf{x}_{k'}^0, y_{k'}^0, \mathbf{s}_{k'}^0; \mathbf{0}^N, 0, \mathbf{g_s})$, we need to change also the second constraint to have[18]

$$
\overrightarrow{D}_Q^0(\mathbf{x}_{k'}^0, y_{k'}^0, \mathbf{s}_{k'}^0; \mathbf{0}^N, 0, \mathbf{g_s}) = \max\ \beta :
$$

$$
\begin{aligned}
\sum_{k=1}^{K} z_k y_k^1 &\geq y_{k'}^0, \qquad (4.11)\\
\sum_{k=1}^{K} z_k s_{km}^1 &\geq s_{k'm}^0 + \beta \mathbf{g_s},\ m = 1, ..., M,\\
\sum_{k=1}^{K} z_k x_{kn}^1 &\leq x_{k'n}^0,\ n = 1, ..., N,\\
z_k &\geq 0,\ k = 1, ..., K.
\end{aligned}
$$

Notice that for the construction of our quality indicators, the direction vector $\mathbf{g}_s$ has to be specified. One possibility is to consider the direction given by the observations, i.e., $\mathbf{g_s} = \mathbf{s}_{k'}$. In this case, we have a measure which is directly related to the Shephard (radial) quality distance function, and to the Malmquist index, that is to say a measure with which readers might be more familiar.

In addition, we use two other direction vectors. First, we consider the *average* attributes content of the grapes for the whole sample of firms, i.e., $\mathbf{g}_s = \overline{\mathbf{s}}_m$, where $\overline{\mathbf{s}}_m = \sum_{k=1}^{K} \frac{s_{km}}{K}$ and $m = 1, .., M$. Another direction we consider is given by the *ideal* composition of the intermediate good. According to industry practitioners,

[18] In this case we get the same results for each observation since we compare the reference observation, i.e., the “base”, to itself K times.

for some raw commodities it is important to have a well balanced composition. For this reason, we compute also the Luenberger indicator in which the direction vector is represented by the ideal composition of the grapes.[19]

The choice of the reference observation (the *base*), to have the 0-technology, allows for different options. One could use the average of the observations, i.e., compare the single observations to the "average firm" (Balk, 1999: 183) defined by:

$$\begin{aligned} \mathbf{s}^0 &= \sum_{k=1}^{K} \frac{s_{km}}{K}, \quad m = 1, ..., M, \\ \mathbf{x}^0 &= \sum_{k=1}^{K} \frac{x_{kn}}{K}, \quad n = 1, ..., N, \\ y^0 &= \sum_{k=1}^{K} \frac{y_k}{K}. \end{aligned}$$

The drawback of this option is that it may lead to an unrealistic artificial technology, or, in other words, to a not feasible input/output combination. Another possibility could be the minimum quality composition required by the law or by industry standards, the one that all firms should provide as a minimum requirement. Or one could choose other bases. However, the point to bear in mind is that any of these choices is arbitrary and should be made according to the problem at hand. In this study we compare each observation to the "average firm" mainly for expositional convenience. Since the production process depends on the weather and other conditions over which the firms have only partial control, we believe that having a base that is the average of the observations, and hence a "moving" reference, is better suited to illustrate how different firms relate to each other. The alternatives, like for instance the minimum required standard set by the industry, would probably be better suited if one were interested also in seeing the effects of different environmental conditions on the ability to reach these standards.

[19] For the case at hand, as for the ideal composition, we consider the maximum amount of sugar in the sample. Indeed, sugar is always preferred in greater quantity, i.e., the more the better, since it could be a limiting factor for the quality of wine. In addition, we set the values for pH, total acidity, potassium, malic and tartaric acidity equal to the ideal values indicated in the literature and by the industry. For Chardonnay (plain), we have total acidity=7, pH=3.2, tartaric acidity=6, malic acidity=2, potassium content=1.8. For Merlot (for aging vintages), the values are the following: sugar=max in the sample, total acidity=5.8, pH=3.1, tartaric acidity=6, malic acidity=1, potassium content=1.9 (Bertamini, 2001).

As a last possibility to consider, and choice to be made, we compute the directional quality distance functions for the construction of the quality indicators considering also a technology weakly disposable in quality attributes. In other words we calculate and compute, for instance, eq. (4.8) modified in the following fashion

$$
\begin{aligned}
\overrightarrow{D}^1_Q(\mathbf{x}^1_{k'}, y^1_{k'}, \mathbf{s}^1_{k'}; \mathbf{0}^N, 0, \mathbf{s}^1_{k'}) = \max\ \beta : & \\
\sum_{k=1}^{K} z_k y^1_k &\geq y^1_{k'}, \\
\sum_{k=1}^{K} z_k s^1_{km} &= s^1_{k'm}(1+\beta),\ m = 1, ..., M, \\
\sum_{k=1}^{K} z_k x^1_{kn} &\leq x^1_{k'n},\ n = 1, ..., N, \\
z_k &\geq 0,\ k = 1, ..., K,
\end{aligned} \tag{4.12}
$$

where the second constraint now has an equality sign. Notice also that for this linear program formulation we have chosen $g_{\mathbf{s}} = s^1_{k'm}$, i.e., a direction in the quality attributes space equal to the observations. It is worth reminding the reader that with weak disposability of outputs, it is only with the choice of a direction vector equal to the observation that the directional distance function is a proper representation of the technology. In other words, when $g_{\mathbf{s}}$ is equal to the average or to the ideal composition of grapes, we cannot be sure on whether from the directional quality distance function one can recover the true technology. However, we report also these results for illustrative purposes.

In summary, we will compute six different quality indicators. Three of them with a strong disposable (in quality attributes) technology, with a direction vector equal to the observations (call it "regular"), to the average ("average"), or to the ideal composition ("ideal"). The other three would have a WDO (in quality attributes) technology, and with the same direction vectors as before, i.e., regular, average, and ideal.

4.3. The quality-quantity trade off

To investigate the relationships between the production level and the different quality attributes, we proceed along two different venues. First, we consider each quality attribute and output individually and we construct the output transformation curve, i.e., the isoquant in output or quality space. To do so, we first calculate a modified version of the directional output distance function in eq.(4.3) for a fixed level of inputs, output or quality attributes. Indeed, since we work on a two-dimensional space, to represent the product transformation curve, for instance, between the production level and the sugar content, we need to hold all the inputs and the other quality attributes at a fixed level, e.g., at their mean value. For instance, for the construction of the output transformation curve between output level (y) and sugar content (s_1), we run the following

$$\overrightarrow{D}_O(\mathbf{x}_{k'}, y_{k'}, \mathbf{s}_{k'}; \mathbf{0}^N, y_{k'}, \mathbf{s}_{k'm}) = \max\ \beta : \tag{4.13}$$

$$\begin{aligned}
\sum_{k=1}^{K} z_k y_k &\geq y_{k'}(1+\beta), \\
\sum_{k=1}^{K} z_k s_{km} &\geq s_{k'1}(1+\beta), \\
\sum_{k=1}^{K} z_k \overline{s}_{km} &\geq \overline{s}_{mk'},\ m = 2, ..., M, \\
\sum_{k=1}^{K} z_k \overline{x}_{kn} &\leq \overline{x}_{k'n},\ n = 1, ..., N, \\
z_k &\geq 0,\ k = 1, ..., K,
\end{aligned}$$

in which we expand the two outputs under consideration, holding the inputs and the other outputs at their mean value, respectively $\overline{x}_n$ and $\overline{s}_m$, with $m = 2, ..., M$. We then find the points on the output transformation curve by multiplying each observation, i.e., y_k and s_{k1}, by $(1+\widehat{\beta}_k)$, where $\widehat{\beta}_k$ is the calculated individual distance from the frontier. Notice that the technology in eq. (4.13) above is specified with constant returns to scale and with output strong disposability. As a further investigation, we calculate and represent the output transformation curve for an output weak disposable technology.[20] We then illustrate the output transformation curves for the main outputs referring to both technology specifications.

For the second investigation, that is to evaluate the trade-off between output quantity and *aggregate* quality, a natural choice is to look at the relationship

[20] In this case, the first and second constraint of eq. (4.13) becomes an equality.

between the quality indicators introduced in this study and the yields. To do this, we consider the different options used for the direction vector $g_{\mathbf{s}}$, and a technology with weakly disposable output and quality attributes, i.e., the most flexible technology, and we show the relationship via a graphical representation and by looking at how the value of the indicators change with yields.

As a further investigation, using the directional distance functions, we construct another quality aggregator extending that proposed by Jaenicke and Lengnick (1999). Considering the directional distance function of eq.(3.1), if we assume that quality is multiplicatively separable from inputs and quantity level, we can have the following

$$\overrightarrow{D}_O(\mathbf{x},y,\mathbf{s};\mathbf{0}^N,g_y,\mathbf{g_s}) = S(s)\ \overrightarrow{D}_O(\mathbf{x},y;\mathbf{0}^N,g_y), \tag{4.14}$$

where $\overrightarrow{D}_O(\mathbf{x},y;\mathbf{0}^N,g_y)$ is the directional output distance function computed without considering the quality attributes, i.e., considering only quantity level, and $S(s)$ is an aggregator reflecting overall aggregate quality. $S(s)$ can be calculated by computing the two distance functions in eq. (4.14), with and without quality attributes, and thus taking their ratio, for each observation. The program to solve for $\overrightarrow{D}_O(\mathbf{x},y,\mathbf{s};\mathbf{0}^N,g_y,\mathbf{g_s})$ is the following[21]

$$\overrightarrow{D}_O(\mathbf{x}_{k'},y_{k'},\mathbf{s}_{k'};\mathbf{0}^N,g_y,\mathbf{g_s}) = \max\ \beta :$$

$$\begin{aligned}
\sum_{k=1}^{K} z_k y_k &= y_{k'} + \beta g_y, \\
\sum_{k=1}^{K} z_k s_{km} &= s_{k'm} + \beta \mathbf{g_s},\ m = 1,...,M, \\
\sum_{k=1}^{K} z_k x_{kn} &\leq x_{k'n},\ n = 1,...,N, \\
z_k &\geq 0,\ k = 1,...,K,
\end{aligned} \tag{4.15}$$

while the program for $\overrightarrow{D}_O(\mathbf{x},y;\mathbf{0}^N,g_y)$ would be the same without the constraint for the quality attributes.

[21] Notice that according to the results of the disposability tests, to be seen later in the text, we impose weak disposability of outputs, i.e., the most flexible technology.

To have different quality aggregators $S(s)$, we compute different versions of eq. (4.15) by using *i*) $g_s = \mathbf{s}_{k'}$ and $g_y = y_{k'}$, that is the direction vector which makes the directional distance function directly comparable (see eq. 3.3) to the radial distance function, i.e., the "regular" distance function; *ii*) the "average" directional output distance function, with ($g_s = \overline{\mathbf{s}}_m$, $g_y = y_{k'}$), thus computing the directional output distance function moving in the direction given by the average content of grapes; and *iii*) the ideal directional distance function ($g_s = ideal$, $g_y = y_{k'}$), i.e., moving in the direction given by the ideal composition of grapes.

Notice that to have an aggregator function that is increasing with quality, it is better to calculate and use $1/S(s)$: it is related to the overall ability of each observation to produce all outputs, i.e., $\mathbf{s}$ and y, in $\overrightarrow{D}_O(\mathbf{x}, y, \mathbf{s}; \mathbf{0}^N, g_y, \mathbf{g_s})$, or to produce only quantity, in $\overrightarrow{D}_O(\mathbf{x}, y; \mathbf{0}^N, g_y)$. Hence the ratio $1/S(s)$ can give an idea of how "costly" it is in terms of reduced production levels to produce more quality attributes. In addition, we can see how the quality aggregator is related to the production level by looking at its plot against yields.

5. The Data

To implement empirically the methodology presented in the previous sections we use data provided by the "Istituto Agrario di San Michele all'Adige", located in Trento, near the Alps, in the North-East of Italy, about 200 miles from Venice. During the last few years, different trials were undertaken to investigate the best agronomic practices and varieties to match the potential of different production zones. The data we employ were collected during the years 1994, 1995 and 1996 for Chardonnay, a white grape variety, and Merlot, a red grape one. The data set is an unbalanced panel: some of the observations are found in different years, but due to incomplete and missing data to have a balanced panel would lead to too few observations.

Thus we treat each observation individually in a series of cross-section estimations, one for each year. In other words, we cannot use the panel dimension for all the observations and hence we consider each variety with a cross section of data, repeating the estimations for the three years for which data is available. For Chardonnay the number of observations with complete data is greater than Merlot: for the white variety we can use n=614 total observations, divided in 214, 187 and 213 respectively for the years 1994, 1995 and 1996. For Merlot, the total number of 325 observations is divided, over the three years considered, respectively, in n=78, 127 and 120.

The data available are experimental agricultural data, in the sense that the purpose of the trials was to estimate the effect of different production areas on grape production subject to the same agronomic practices regarding labour, fertilizer, pesticides, etc. In other words, all parcels were treated with the same amount of fertilizers, pesticides, labour, etc. For each parcel, data are available on altimetry, the number of vines per hectare, and the number of buds per branch. In addition, there are three categorical variables: the depth of the roots (a measure of the depth of usable soil), from a minimum of 1 to a maximum of 3; the water reservoir, in the range 1-4; and total calcium, starting from a minimum of 1 to a maximum of 5 (tables 1-A and 1-B).

[Insert Tables 1-A and 1-B about here]

We also have data on weather conditions, but it is coming from a unique meteoric station, and so we have only variation over the years. However, as it is standard practice among practitioners, only the conditions of the last 40 days before harvest time are considered important and hence used in this study. In the period 1994-1996 that we consider, harvest time was about the first week of September for Chardonnay, and the third week of September for Merlot, with a lag between the two varieties of 12-18 days, depending on the year. Since harvest time is different, we in fact have different data on weather conditions between the two varieties. The information available for weather conditions are related to humidity and temperature, measured as the average of the 40 days considered. In addition, rainfall, radiation, hours of sun, and temperature excursions,[22] are all considered as the total summation over the last 40 days before harvest time (tables 1-A and 1-B).

For the grapes obtained in the different experimental fields, we have data on production per hectare plus other information on different attributes, such as sugar content (measured in degrees Brix), tartaric acid, malic acid, potassium, pH, and total acidity (tables 1-A and 1-B).

5.1. Chardonnay

On average, Chardonnay trials were conducted on higher fields compared to Merlot: the average height above the sea level was around 260 meters against above 200 for Merlot. It is well known among practitioners that in general Merlot is more

[22] Temperature excursion is the difference between the maximum and the minimum daily temperature.

productive than Chardonnay. This explains that the number of vines per hectare was higher for Chardonnay, around 3200, compared to 2700 for Merlot. This latter variety, however, presented more buds per branch over the years. For the roots depth, water reservoir and total calcium, there were not significant differences between the two varieties and not much variations over the years considered.

Weather conditions show that for Chardonnay in 1994 the pre-harvest season was hot – a mean temperature of 22° C – with low humidity, relatively rainy but with high radiation, sun hours and temperature excursions. In other words, 1994 was relatively hot and dry, a situation which practitioners normally associate with a good harvest in terms of sugar (and hence alcohol content in wines). On the other hand, 1996 was more humid, colder and with low radiation, sun hours and temperature range, a situation in which it may be easier to find higher acidity in the grapes for the wine production. The year 1995 presented weather conditions that were something in between those of 1994 and 1996, with particularly low rainfall.[23] (Table 1-A)

On the production side, in 1994 Chardonnay presented an average yield (14.5 t/ha) but relatively high in sugar content and low in total, tartaric and malic acidity, and in potassium content, as one would have expected by looking at the weather conditions of the pre-harvest season. In 1996, on the other hand, the higher yields (mean of 18.2 t/ha) presented less sugar content but more total, tartaric and malic acidity, and potassium content. In 1995, Chardonnay had the lowest average yield with more total acidity and high malic acidity.

To summarize, looking at Chardonnay over the period of three years, one may conclude that in the area under consideration high temperatures led to production with more sugar content and less acidity, while a more humid and colder weather led to more production but with less sugar content and more acidity. Thus considering the limitations of looking at only the means of the observations, one may argue that there is a trade-off between sugar and yields, on one hand, and sugar and total acidity on the other.

5.2. Merlot

Although there was a difference of about two weeks, the weather in 1994 for Merlot was like that of Chardonnay (this is not the case, as we will see shortly, for 1995 and 1996). Thus 1994 was relatively dry but rainy, with relatively high temperatures (20.7° C on average) and high radiation, sun hours, temperature

[23] We do not have information on whether irrigation was possible and practiced in these plots.

excursions. 1995 and 1996 were relatively similar in terms of weather conditions: however, 1995 was most humid and with the lowest of radiation, sun hours, and temperature excursions. 1996, on the other hand, had the lowest rainfall and average temperature.

On the production side, 1995 was the year in which yields were the lowest but sugar content and acidity were the highest, together with tartaric and malic acidity. Potassium content, on the other hand, was the lowest of the three years under consideration. In 1996, potassium content and yields were the highest but sugar content and tartaric acidity the lowest. In 1994, production for quantity and quality attributes was between that of 1995 and 1996, but with the lowest levels of total and malic acidity. To conclude, one may summarize the situation for Merlot by noting that the colder weather conditions led to high production levels, with potassium but not sugar content. In addition, low radiation, temperature range and sun hours led to both sugar and acidity. With all the cautions needed when considering only average data, it seems that sugar and acidity are not output-substitutes for Merlot, differently from Chardonnay, at least in 1995 when they both reached the highest level.

We pay a closer look at production, sugar content, total acidity and potassium content, since they are among the important aspects of grapes production, looking also at their distribution.[24] Overall, Merlot is more productive in terms of both grapes production and sugar content (figures 3 and 5). Considering the production per hectare of grapes over the entire period, Merlot is statistically more productive than Chardonnay (1% significance level (s.l.)), but in 1995, the year with the lowest production level, there were no statistically significant differences between the two varieties (figure 3). It then appears that when weather conditions are not the ideal ones, the red and the white grape variety under consideration do not show big differences in terms of yields. On the other hand, when there are favorable conditions, Merlot shows all its potential and produces significantly more than Chardonnay. Indeed, the year 1996 appears to have been the most productive year for both varieties (figure 4), with Merlot reaching an average of 22 tons per hectare (up from 14 in 1995) and Chardonnay reaching 18 tons/ha (up from 13 in 1995, see also tables 1-A and 1-B).

[Insert Figures 3-6 about here]

[24] The figures 3-10 show kernel estimates. To test the differences between cultivars or years we performed the Mann-Withney test of equality of medians and the Kolmogoroff-Smirnoff test of equality of distributions. Results of the tests are reported in the kernel figures. All figures and tests were prepared using Stata 7.

Merlot, as expected, is more productive also in terms of sugar content. Over the period 1994-1996 and for each year considered, Merlot has statistically significant more sugar than Chardonnay (figure 5), with a significance level of 1% (except in 1994, the best year for sugar production in Chardonnay but only an average year for Merlot, when s.l.=5%). Opposite to the case of production per hectare seen above, however, 1996 is the year with the lowest sugar content (figure 6 and tables 1-A/B). Even though we are considering average data, it appears that yields and sugar go in opposite directions, i.e., they are substitutes, and when conditions are very favorable to one they are not favorable to the other.

The differences between varieties are statistically significant also with regard to total acidity and potassium content. Chardonnay shows consistently significant more total acidity than Merlot (figure 7). For both varieties, the worst year for acidity is 1994, which is however the best for sugar production, at least in Chardonnay. Their best for acidity, however, is 1995 for Merlot and 1996 for Chardonnay (figure 8). For potassium content, Merlot, over the period 1994-1996 and for each year considered, contains significantly (s.l. at 1%) more of it than Chardonnay (figure 9). For both varieties, 1994 is the year with the lowest mean values, while 1996 is that with the highest (figure 10).

[Insert Figures 7-10 about here]

Total acidity and potassium content thus appear to be associated with the production level, i.e., they seem complement with yields. Indeed, in 1996 the data show a very high production of grapes but with lower sugar content: Merlot contains 19.8 degrees Brix, down from an average of 20.5° in 1995, while for Chardonnay sugar content in 1996 was 19.2° Brix, down from 19.9° in 1994. In 1996, the production level and the content of potassium are highest for both cultivars, as well as total acidity for Chardonnay, compared to the other two years considered (figure 8).

6. Results

In the sections that follow we report the results of the different computations and estimations. We begin with the results on the returns to scale and the disposability properties of the technology, computed with the directional output distance function with the direction vector equal to the observations, i.e., to make it comparable to the radial output distance function, and we test for differences among the different specifications via the KS and the MW tests. Then we report the results on the Luenberger quality indicators. In the last sections, we show the findings of the analysis on the quality-quantity trade-off. All computations were performed for each variety and each year (cross-section). For all the results, we distinguish between the two cultivars, Chardonnay and Merlot.

6.1. Analysis of Chardonnay

6.1.1. The Returns to Scale and Disposability Properties of the Technology

To characterize the properties of the technology emerging from the sample of observations under consideration, we first consider the **returns to scale**. We compute the directional output distance function in eq. (4.3) and its variable returns to scale specification, i.e., with the last constraint changed to $\sum_{k=1}^{K} z_k = 1$. Using the KS and MW tests introduced above, we cannot reject the null that the two different specifications have the same distribution (table 2). Indeed, for each of the years considered, the calculated test statistics, for both MW and KS tests, are well above the usually employed significant levels. For Chardonnay, the technology for each year thus appears to have constant returns to scale. This is not surprising if we consider that each observation comes from an experimental plot, and that all the plots are more or less of the same size. In other words, the relative size of the experiments is relatively homogenous, without big variations among plots, and this may explain the constant returns to scale properties of the technology.

[Insert Table 2 about here]

To better characterize technology, we also look at the **output disposability properties** of the sample of observations under consideration. While we do not have a priory reasons to expect congestion on the input side, i.e., no need to test for input weak disposability, on the output side we decide to perform the tests to see whether the technology presents either strong or weak output (or quality attributes) disposability.[25] As explained in the preceding sections, first we test A) whether jointly all outputs are weakly disposable. Then we test B) whether

[25] In this study we are mostly interested on the output side of production. In addition, the nature of the input data would probably not allow any meaningful test of input disposability.

each output taken individually is weakly disposable. Finally, we investigate the relationship of each quality attribute with the production level (test C)).

Regarding the first test A), the joint test of output disposability, the results reported in table 2A (first column) show that for all the years considered the probability of error in saying that the two distributions are different is nil. In other words, we can reject the null that for Chardonnay the technology is strongly disposable for output and quality attributes jointly. It thus appears that the technology is weakly disposable in all outputs for all the years considered. Taken all together, the outputs thus appear to be complements in production.

[Insert Table 2A about here]

Regarding the test B), on the disposability properties of each output component, we can see that we cannot reject the null that the **yields** are strongly disposable in the three years considered. For Chardonnay, it thus appears that the level of production, i.e., the yields, are substitute with other outputs, that is the quality attributes, [26] a result which is not surprising. For the other outputs, i.e., quality attributes, the results are more varied. **Sugar** appears to be strongly disposable for all the years considered. Remembering that strong disposability implies substitutability among outputs, while weak disposability can also be used to model complementarity among outputs, this result shows that the major quality component of grapes, i.e., the necessary ingredient for alcohol content, is a substitute with other outputs. This is not surprising, since it is well known that Chardonnay is a white variety with relatively lower yields and sugar potential. In addition, it may be grown in colder climates to give wines rich in acidity and relatively low in alcohol.

Looking at **total acidity**, the results in table 2A show that it is mostly strongly disposable. Only in 1996, the MW test shows weak disposability, while the KS shows strong disposability. Thus, for most of the years considered, total acidity appears a substitute with others outputs, while for 1996, based on one of the two statistical tests performed, it appears to be a complement. Related to weather conditions, one may argue that with colder years – by practitioners usually considered more likely to lead to more acid grapes in white varieties such as Chardonnay – total acidity is more easily obtained, jointly with other outputs, i.e., it is weakly disposable. In hotter years, however, acidity is an output substitute with other

[26] In table 2A, in bold are reported the calculated tests when they result below the 10% significance level.

quality attributes and production level, i.e., it is strongly disposable. Notice indeed that in 1994 the weather was hotter and dry, thus more favorable to sugar content than to acidity in grapes. This may explain why total acidity appears strongly disposable, i.e., a substitute, with other outputs, in this year. On the other hand, the weather in 1996 was cold and more humid, i.e., more favorable to production and acidity, and this may explain the fact that total acidity appears to be a complement with other outputs, i.e., weakly disposable, in its favorable year.

pH, a measure of the acidity of grapes, appears strongly disposable for all the years considered.[27] Regarding **tartaric acidity**, notice that only in 1994, when performing a MW test, it results weakly disposable, otherwise it appears to be strongly disposable. Both **malic acidity** and **potassium content** result weakly disposable for all the years considered, with the only exception for K content in 1994 according to the KS test. We thus may conclude that malic acid and potassium content are complements or joint with the other outputs, and that increasing yields, for instance, goes together with increasing malic acidity and potassium content. This joint ness, however, may be undesirable when one quality attribute is not very valuable in a particular commodity. This is the case, for instance, for potassium content, which sometimes is preferred in limited amounts when preparing some particular wines. In Chardonnay, the tests show that reducing potassium content, according to the observations in the period 1994-1996, would require also the reduction of other outputs.

To summarize, the investigation of the disposability properties of Chardonnay, a white wine variety which may prefer a relatively cold weather where it can produce relatively acid wines, shows that most of the quality attributes and production levels are strongly disposable, i.e., substitutes, in the production process. Only malic acidity and potassium content are weakly disposable, i.e., complements in the technology.

As a further exploration, we look at the relationship between each quality attribute and the production level. We performed thus the tests outlined in C), for which results are reported in tables $2B - 2C$, and we summarize the findings in table $2D$.[28] First, notice that the results in table $2D$ replicates those in table

[27] In a scale from 0 to 14, a pH of 7 indicates a neutral environment. A pH below 7 indicates acidity, while one above 7 shows alkalinity.

[28] The results of table $2D$ summarize the tests C). Consider for instance total acidity for Chardonnay in 1994. The resuls of table $2B$ show that we can reject the null that total acidity and yields are jointly weakly disposable, when tested against the alternative that only total

$2A$:[29] malic acidity and potassium content are weakly disposable with y, meaning that their presence implies a considerable production level, but not necessarily the reverse. Looking at it another way, it means that potassium and malic acidity are joint with production, and reducing either one of them would need to be accompanied by a reduction of production level or by an increase in inputs use.

[Insert tables 2B-2C-2D about here]

Sugar, pH, and tartaric acidity, on the other hand, result strongly disposable, i.e., substitutes with production, for all the years considered. In other words, obtaining a high yields level would imply lowering their content. Total acidity appears always strongly disposable with production level, apart from 1996, a colder year in which total acidity (partially, i.e., with the MW test) appears weakly disposable with production, i.e., complement with the production level.

6.1.2. The Quality Indicators

Given the results of the previous section, we compute the directional quality distance functions needed for computing the quality indicators with a constant returns to scale technology. Indeed, according to our results we can infer that the technology of our observations is consistent with such a technology. Regarding the output disposability properties, however, we calculate and compare the three Luenberger quality indicators using both strong disposability and weak disposability of quality attributes.[30] We report the summary results of the different computations performed for each observation using different methodologies.

As a benchmark, we report first the results of the Luenberger quality indicator computed with a direction vector equal to the observation ("regular") to make it directly comparable to the Malmquist quality index, for different years. Tables 3A and 3B report some descriptive statistics for the Luenberger "regular" quality

acidity is weakly disposable. In table $2C$, we reject the null that total acidity and yields are jointly weakly disposable, on the other hand, when tested against the alternative that only yields is weakly disposable. Combining these two results confirms that total acidity and yields are mutually strongly disposable, i.e., substitute, as summarized in table $2D$.

[29] As we will see, this is not the case for Merlot, for which there are some differences.

[30] Regarding this latter, we use weak disposability for all quality attributes instead of imposing it only to those for which the previous disposability tests showed weak disposability because it is the most flexible technology we can refer to. The alternative would be to impose WDO only for those attributes for which the disposability tests did in fact show it to be the true specification. The results however would not be significantly different.

indicator, respectively with a (quality) strong and weak disposable technology, and figures 11A and 11B show the kernel estimates of the distributions. We then report the Luenberger quality indicators, with the average direction ("average"), when quality attributes are strongly (table 4A) or weakly disposable (4B). Last, we show the results of the Luenberger indicators with the direction vector equal to the ideal composition ("ideal"), again with strongly disposable (table 5A) and weakly disposable (5B) quality attributes.

Starting with the Luenberger "**regular**" quality indicator, first of all notice that in almost all cases the index is above zero, meaning that on average the quality of the firms under consideration is higher than the average firm taken as a reference. This means that a majority of observations have an indicator, i.e., a quality content, above that of the average firm. This may surprise the reader, but the average firm taken as a term of comparison is an "artificial" one, in the sense that it was constructed by taking the average of the observations over all the input and output dimensions. Thus it may well be that the "average" firm, when using a multidimensional comparison, in fact may result being below the average of the individual observations, i.e., comparisons.[31]

Considering the Luenberger "regular" quality indicator computed referring to a strongly disposable technology, the year 1995 seems the most favorable, in the sense that the mean quality indicator is above that of the other years considered. It also presents the lowest dispersion, i.e., the smallest standard deviation. 1994, on the other hand, shows the lowest average value for the indicator, and a higher dispersion. When the "regular" quality indicator is computed using an output weakly disposable technology, its average values increase together with their dispersion around the mean value. Again, 1995 has the highest average, 1994 the lowest. That referring to a weakly disposable, i.e., a more flexible technology, leads to an increase in efficiency, should not come as a surprise. Indeed, for the individual observation, the distance from the frontier with WDO cannot be greater than that with SDO.[32]

[Insert Tables 3A-3B about here]

In the second Luenberger indicator computed, the direction we consider is that equal to the **average** attributes of the group of firms (tables 4A and 4B).

[31] For instance, in 1994 there are 103 out of 214 observations that have a negative indicator, while the remaining 111 have a positive quality indicator.

[32] In terms of figure 2, the observation s^0 is closer to the frontier of the weakly disposable technology (0EBCD) than to the SDO frontier (0ABCD).

Relative to a technology strongly disposable in all outputs, the sample of firms under consideration have more quality than the average firm, i.e., the indicator is positive. Again, 1995 is the year with the highest mean values for the quality indicator, showing also that the aggregate quality indicator is the least dispersed. On the other hand, when referring to a weakly disposable technology, the year with the best average value of the quality indicator becomes 1996, with an average very different from those of the other years. In addition, when going from a strong to a weakly disposable representation of the technology, the average value of the indicator decreases for 1995 and increases for 1994 and 1996. Thus, with the Luenberger quality indicator based on the average direction, Chardonnay shows that referring to a weakly disposable technology does not always lead to better average values.

[Insert Tables 4A-4B about here]

Considering the **ideal** composition instead, apart from 1994, the Luenberger indicator seems to show lower quality than the previous Luenberger indicator based on the average of the observations, suggesting that on average the group of firms is doing worse when evaluated with reference to a direction equal to the ideal composition (tables 5A and 5B). This is understandable, since instead of moving in an "average" direction we move towards the efficient frontier of the technology along the direction given by the ideal composition of the grapes, and hence a presumably more difficult venue to follow for the firms under consideration. We can then observe that, using a strongly disposable specification of the reference technology, in 1994 the sample of observations considered is on average performing better than the average firm, while in 1996 is performing worse and obtaining on average the same quality performances in 1995.

When referring to a technology weakly disposable in outputs, the average values for the quality indicator increase for 1994 and 1996, and remains the same in 1995. Again, like for the radial quality index, and more than with the Luenberger quality measures based on the average direction, when the distance is measured from a frontier more tightly enveloped, like in the case of weak disposability, the efficiency should not decrease.[33]

[Insert Tables 5A-5B about here]

[33] This intuition is correct if we refer to the distance in $\overrightarrow{D}^1_O(\mathbf{x}^1,y^1,\mathbf{s}^1;\mathbf{0}^N,0,\mathbf{g_s})$. When referring to the distance $\overrightarrow{D}^0_O(\mathbf{x}^0,y^0,\mathbf{s}^1;\mathbf{0}^N,0,\mathbf{g_s})$ or $\overrightarrow{D}^1_O(\mathbf{x}^1,y^1,\mathbf{s}^0;\mathbf{0}^N,0,\mathbf{g_s})$, however, things are not so straightforward and intuitive.

As a further representation of the results, we show the **distributions** of the different quality aggregators using a kernel approximation. In figure 11A we see the three measures for different years using a **strongly disposable** representation of the technology. All distributions appear rather similar among them, with some differences across years. For instance, in 1994 the distributions have a unique mode around the value of 0, and a bigger dispersion of the values above 0, i.e., a longer tail on the right. On the other hand, in 1995 the distribution of the different quality aggregators is still asymmetric but with more dispersion on the left side, i.e., for the values below 0. In 1996 the three distributions are rather symmetrical (figure 11A).

Performing the statistical test suggested by Banker, the Kolmogorov-Smirnoff (KS), we find only limited statistically significant differences among the three distributions of the quality aggregators based on a strongly disposable technology (table 6). Indeed, both the Luenberger average and ideal quality indicators are not different from the Luenberger regular quality indicator. In addition, the distribution of the Luenberger indicator based on the average direction does not appear different from that of the ideal Luenberger indicator for all the years considered. Thus the three measures seem to give the same results when evaluating the quality attributes of different observations using a strong disposable specification of the technology.

More diverse appear the distributions of the different quality productivity measures when computed with reference to a **weakly disposable technology** (figure 11B). First of all, the distributions, especially those of the regular Luenberger indicator in different years, appear to be bimodal, with a second mode to the right of the principal mode centered around 0, the mean value. In addition, the regular indicator distributions appear rather different than the other two Luenberger ones, much more than with a strongly disposable technology. Indeed, the results of the KS test show that with weak disposability the distributions are different. In particular, both the ideal and average Luenberger indicators distributions are different from the regular Luenberger's distributions. However, the average Luenberger indicator distribution is not different from that of the ideal one in any of the three years considered (table 6).[34]

[Insert figures 11A and 11B about here]

[34] Notice however that, as explained in the text, with WDO and the direction vector equal to either the average or the ideal composition of grapes, we are not sure on whether we can recover the true technology from the directional distance functions.

The comparison of the distributions obtained with strong disposability to those referring instead to weak disposability shows that results are again different. The regular indicator with SDO is different from that computed with a WDO technology for all the years considered. On the other hand, for the average and ideal Luenberger indicators, their distributions are different when using different disposability properties of the technology, in 1994 and 1996. In 1995, using a strong or weak disposable technology does not seem to lead to different results for the quality indicators (table 6). To summarize, with Chardonnay the quality indicators show that results may vary over the years and across the different measures. In addition, and perhaps most important, it is necessary to correctly specify the technology, since results may vary considerably.

6.1.3. The Quality-Quantity Trade off

The results summarized in table $2D$ are interesting also for the individual trade-off, that is the relationship between individual quality attributes and the production level. Results vary across years, but one can notice that, for most of the years, in Chardonnay sugar, total acidity, pH and tartaric acidity are substitutes with yields. Thus greater yields may come at the expenses of these quality attributes. On the other hand, malic acidity and potassium content are complement with production levels. In particular, if one were required to have a lower potassium content, it would presumably need to reduce production levels as well.

To investigate further the relationships among individual quality attributes and yields, we look at the output transformation curves and at the output sets of some of the major quality components. We now present the results looking at the differences across years, across cultivars, and across technology specifications. Starting from the output transformation curves between **yields** and **sugar**, in figure 13 we show the differences across years with a technology strongly disposable in outputs. For Chardonnay, given the position of the frontiers, one could argue that 1996 is a good year for yields while 1994 is a good year for sugar content. Indeed, the output set for 1996 is the furthest to the right, i.e., associated with higher production levels, while that of 1994 is the tallest.[35] Notice also that in 1996 higher yields seem to come at the expense of lower sugar content, given

[35] Notice however that there are only few observations generating the vertical tract of the frontier and thus it could be that the mean values for the yields are lower in 1996 than 1994. For sugar content, on the other hand, the horizontal tract is generated by many observations and hence it is reasonable to expect that year with the highest values, i.e., 1994, which has the tallest frontier, should have also higher mean values for sugar content.

that the output frontier is the shortest in the vertical dimension, that is with less sugar content. Also notice that the output set of 1995 is included in that of 1994, meaning that the production frontier in 1995 was lower for both dimensions compared to 1994.

Another set of considerations, which can be derived also from figure 14, can show that the trade-off between sugar and yields, which corresponds to the output isoquant with a negative slope, begins at different production levels according to the year. In 1994, the best for sugar, the trade-off begins just at around 10 t/ha, in which sugar content is above 22° Brix, reaching about 20° Brix at around 25 t/ha. In 1995, the trade-off begins at around 15 t/ha with slightly less than 22° Brix, but the decrease is much faster: at 23-4 t/ha, sugar content is around 19° Brix. In 1996, the substitutability between sugar and yields begins at around 13-4 t/ha, with less than 22° Brix, but the minimum of 19° Brix is only reached at around 30 t/ha. Thus the trade-off between sugar and yields is different in intensity and extension according to the year and its relative weather conditions. In 1995 the yields were the lowest of the three years considered, and this can be seen also from the fact that the output set of this year, the one that represents yields and sugar, is included in that of 1994.

In figure 14 we report the comparison with Merlot for each year. Notice that for 1995 and 1996 Chardonnay production frontiers are included in those of Merlot: in other words, Merlot is more productive than Chardonnay for both yields and sugar content. In 1994, however, Merlot is less productive in terms of yields. If we compare different technology specifications, that is the output transformation curves with a weak and a strong output disposable technology, we can see that there are not big differences (figure 15), meaning that presumably the data support the conclusion that yields and sugar content are strongly disposable, confirming what resulted in the disposability tests presented before. For all the three years, however, the left part of the weak disposable frontier appears to be internal to the strong disposable frontier. Even if only slightly, then it then appears that yields are weak disposable with respect to sugar content; in other words, yields seem, over a production range up to around 10 t/ha, complementary to sugar production.

[Insert Figure 13-14-15-16 about here]

Looking at **total acidity** and **yields**, one can notice that the situation for Chardonnay is very different according to the year considered. Indeed, 1996 seems a very productive year, since the frontier is located outside those for the other two years for both yields and total acidity. The worst year is 1994, which frontier is the smallest, i.e., included in those of 1996 and, for acidity, 1995 (figure 17). In 1994, a hot and dry year favorable to sugar production, the production of acidity is indeed the lowest, as can be seen also from the height of the output set, which is the smallest.

Compared to Merlot, Chardonnay appears to be more productive in terms of total acidity for all the years considered, and in 1994 also in terms of yields (figure 18).[36] Looking at the disposability of the technology and comparing the output isoquants derived with a weak and a strong output disposability specifications of the technology (figure 19), one can notice that yields appear complement to total acidity production for all the years, and particularly for 1995, in which yields are complement to acidity up to a production level of about 13 t/ha. Even if much less pronounced, total acidity appears weak disposable with yields in 1994 and 1995.

[Insert Figure 17-18-19-20 about here]

Of some interest appears also the relationship between **sugar** and **total acidity**, even if most of the information has already been gathered from previous figures as well. Notice that the trade-off between sugar and acidity is lower, i.e., the isoquant is flatter, in 1994, when acidity was the lowest, given that the conditions were very favorable to sugar production but not to acidity (figure 21). In 1995 and 1996, indeed, there is a more abrupt drop in acidity once the yields reach around 18 t/ha. Apart from 1994, in the other years it appears that Chardonnay is more productive in terms of acidity, while Merlot produces more sugar (figure 22), confirming the results of the comparison of the distributions seen in previous sections. Finally, representing the isoquants with different disposability specifications of the technology, one can notice that total acidity appears weakly disposable, i.e., complement in production, to sugar for all the years, even if only for a limited range of sugar content (figure 23).

[Insert Figure 21-22-23-24 about here]

Considering **potassium** and **yields**, it is interesting to notice that there are little differences among the different years, i.e., the frontiers are very close in the

[36] In fact, comparing the distributions of the yields we showed that Merlot was on average more productive (even if only at the 10% s.l.) than Chardonnay in 1994. This illustrates that it may sometimes be misleading to compare frontiers derived from few extreme observations.

potassium direction (figure 25). It appears however that the frontier in 1996 is the farthest to the right and the shortest, i.e., more yields and less potassium, while it is the opposite for 1995, meaning that with a strongly disposable specification of the technology yields and potassium content seems to go in opposite directions. Considering however a weak disposable technology specification, the comparison of the output transformation curves shows that for 1994 and 1995 the yields appear weakly disposable, i.e., complement in production, to potassium content (figure 27).

[Insert Figure 25-26-27-28 about here]

Not very visually differentiated across years and between cultivars are the output transformation curves of **sugar** and **potassium content** (figure 29 and 30), while it appears of some interest to consider the comparison between the weak and the strong output disposable specification of the technology. Indeed, in 1995 and 1996 it appears that both sugar and potassium are weakly disposable, while in 1994 only potassium seems weakly disposable to sugar content and not vice-versa (figure 31).

[Insert Figure 29-30-31-32 about here]

To test whether quantity is a substitute with **aggregate quality**, i.e., whether there is a trade-off between quantity and aggregate quality, we look at the relationship between the Luenberger indicators and the yields. As can be seen from figure 33, when the production level increases the quality indicators - the regular, average and ideal - seem to decrease. Indeed, this apparent trend is confirmed when comparing the average values of the indicators at different production levels (table 7A): going from below 10t/ha to above 20 t/ha indeed is accompanied by a reduction of the indicators, which go form positive to negative average values. Only in 1995, for the "ideal" quality indicator, the trend is not monotonic, since the difference in the average values of the indicators between the production level from below 10 to 10-20 t/ha is actually increasing.

[Insert table 7A about here]

As a supplementary test of the trade-off between quantity and aggregate quality, we also compute the quality aggregator of eq. (4.14) and plot it against production level (figure 34). First of all, notice that the three different measures -

based respectively on the radial, directional average and directional ideal distance functions - give very similar results, so similar that they seem to coincide in figure 34. In all the measures, and for the three years considered, there is however a visible trade-off between the production level and aggregate quality as measured by $1/S(s)$, as can be seen also in figure 35 where we compare the quality aggregators computed only with the "regular" directional distance function across years.

Notice also that the relationship is clearly not linear. A bigger decrease in the aggregate quality is for the lower production levels: below 10 t/ha, the quality aggregator shifts from values above 4-5 to around 2-2.5. Notice also that for very low production levels, i.e., below 5 t/ha, there are very high values of the quality aggregator, even above 10 in 1995. Another considerable decrease of aggregate quality is in the production level within the 10-20 t/ha range: the quality aggregator decreases from 3.24-3.50 to 1.19-1.27, thus more than halving (see table 7B). For production levels around 30 t/ha, the quality aggregator tends asymptotically to reach the minimum of 1, which is obtained at different production levels according to the year considered. In 1996, a good year for yields, the minimum is reached for production levels above 30 t/ha, while in 1994 and 1995 the minimum is obtained already at 26-28 t/ha. In other words, for all the production levels up to 30 t/ha, the year 1996 shows higher values of the quality aggregator, confirming that in that favorable year reaching good production levels was less costly in terms of lower aggregate quality.[37]

[Insert Figure 33-34-35 about here]

As already introduced, the EU system for market regulation in the wine sector is based on AOC, which among other things specify that production must be within a certain ceiling. In Trentino, the yield ceiling for Chardonnay (and Merlot) cultivated for AOC wines is 14 t/ha. Corresponding to that production level, the quality aggregator is in the range between 1.61 and 2, with the higher value in 1996. This means that compared to the highest production levels, above 30 t/ha, the overall quality is almost double. On the other hand, compared to lower production levels, e.g., 10 t/ha, the aggregate quality decreases by about 43-53%. Although with this information alone it may be difficult to exactly establish at which production level one should place the production ceiling to get the most appropriate quality level, it is interesting to notice that there are significant

[37] However, notice that comparing the aggregate quality values of different years could be misleading since each measure is based on the sample for that particular year. In other words, it is a measure of relative and not absolute performance.

differences across years and thus an a priory and fixed ceiling on yields may be effective in some years but not in others.

[Insert Table 7B about here]

6.2. Analysis of Merlot

6.2.1. The Returns to Scale and Disposability Properties of the Technology

Regarding our red grape variety, results of the tests for **returns to scale** confirms that, as in Chardonnay, we cannot reject the null hypothesis of constant returns to scale (Table 2). More interesting however are the results on the **output disposability properties** of the technology. Overall, that is testing for all outputs jointly being weakly disposable against the null of strong disposability (test A), we reject the null hypothesis of free disposability, as in Chardonnay. The only exception is in 1994, in which the KS test does not detect any statistically significant difference between WDO and SDO and thus we cannot reject the null of strong disposability of outputs (table 2A).

Considering the disposability properties of each output (test B), we can see that we can reject the alternative hypothesis that the **yields** are weakly disposable in all the years considered. In other words, like in Chardonnay, for Merlot the production level is strongly disposable, i.e., substitute, with other outputs, that is the quality attributes. **Sugar** as well appears to be strongly disposable for all the years considered, thus confirming that (probably) the major quality component of grapes is a substitute for the other quality attributes and production level. Consider however that Merlot is a red variety and has relatively higher yields and sugar potential, contrary to Chardonnay, and thus it may be cultivated in hotter climates to give bodied and strong wines.

Looking at **total acidity**, the results show that it is mostly strongly disposable (apart from 1995, only with the MW test, when weather was colder and yields the lowest of the period under consideration), indeed showing that acidity in Merlot is a substitute for other quality attributes in most circumstances, not an unexpected result when considering a productive red grape variety like Merlot. **pH**, as already seen for Chardonnay, results strongly disposable for all the years considered. Regarding **tartaric acidity**, it results to be strongly disposable. Both **malic acidity** and **potassium** content are weakly disposable for some of the years considered: malic acidity for all the years but only according to the MW test, K content in 1994 and 1995 but again only according to the MW test. With the KS test they result strongly disposable. Thus, although less pronounced than with Chardonnay, in Merlot malic acid and potassium content in some instances are complements or joint with the other outputs.

To synthesize, the disposability properties of Merlot, a red variety preferring hotter weather conditions in which it can produces relatively strong and full bodied wines, show that many of its quality attributes are strongly disposable, i.e., substitutes, in the production process. As in Chardonnay, but in fewer instances, malic acidity and potassium content are weakly disposable, i.e., complements in the technology, and therefore reducing their content in grapes may be obtained only at the expenses of reducing also other outputs. Similar results emerge when considering the disposability properties of each individual attribute considered jointly with yields (table $2D$). Notice that, compared to Chardonnay, in Merlot fewer attributes appear complements (weakly disposable), while most of them are strongly disposable individually or jointly with yields. In words, in Merlot more than in Chardonnay, being the former a more productive variety in terms of yields, many attributes become substitute in the production process.

6.2.2. The Quality Indicators

We report the summary results of the different quality aggregator for our red grape variety. As a benchmark, we begin with the results of the Luenberger "**regular**" quality indicator for different years using a strongly output disposable technology (tables 3A and 3B). In 1994 the observations for Merlot show an average value of the Luenberger "regular" quality indicator which is negative, thus indicating that in the first year considered the observations on average have an aggregate quality lower than the reference observation. In 1995 and 1996, however, the mean value of the indicator is positive, as we have already seen for Chardonnay.

Using a weak disposable technology again increases the mean value of the indicator and its dispersion around the mean for all the years considered (table 3B). Indeed, the increase is pretty significant, and for 1994 the average values of the regular indicator become positive. Thus, like in Chardonnay, referring to a more flexible technology, which we have shown to be the true one, at least for some of the quality attributes, allows the observations at hand to be closer to the frontier.

[Insert Tables 3A-3B about here]

For the Luenberger "**average**" indicator with direction equal to the average attributes of the observations, relative to a strongly disposable technology, the sample of firms under consideration have more quality than the average firm, i.e., the indicator is positive, in 1995 and 1996. In 1994 however, the quality index is below 0, showing that the average quality is lower than that of the reference firm, as already seen with the regular indicator (table 4A).

When referring to a weakly disposable technology, however, results are quite different (table 4B). Indeed, the average values of the indicators do not increase except for the year 1995. For 1994 and 1994 the average values of the indicators decrease and become more dispersed. Thus, with the Luenberger quality indicator based on the average direction, Merlot reinforce the results we have seen for Chardonnay, showing that referring to a weakly disposable technology may actually worsen the average values for the quality productivity measures.

[Insert Tables 4A-4B about here]

Considering the Luenberger indicator with the **ideal** composition as direction, 1994 appears the year with the worst performances, i.e., the mean value of the indicator is negative, implying that the group of firms is doing worse than the reference firm. This appears to be true for both specifications of the technology, that is to say under strong and weak disposability of outputs (tables 5A and 5B). However, with the ideal Luenberger indicator the weak disposability specification of the technology leads to an increase in the mean values of the indicator and a lower dispersion for all the years considered. From this point of view, the Luenberger ideal indicator seems more consistent (or stable) in keeping the ranking across years and across technology specifications, at least when compared to the indicators measured with the regular and the average direction vectors.

[Insert Tables 5A-5B about here]

We also investigate the different quality measures by looking at their **distributions**. In figure 12A, using a kernel approximation, we see the three measures for different years using a **strongly disposable** representation of the technology. The three distributions appear rather similar among them, with some differences across years. For instance, in 1994 the distributions have a mode around the value of 0, a bigger dispersion of the values above 0, and some increase in density just to the left of the mode, i.e., for some values below average. In 1995 the three distributions however are rather symmetrical, while in 1996 the distribution of the different quality measures is asymmetric with a long tail on the right side, i.e., more dispersion for the values above 0.

Looking for significant differences among the distributions by means of the Kolmogorov Smirnoff's (KS) test, we find only limited differences among the three distributions of the quality productivity measures based on a strongly disposable technology: like in Chardonnay, both the Luenberger average and ideal quality indicators are not different from the Luenberger "regular" quality indicator. The distribution of the Luenberger indicator based on the average direction, moreover, is not different from that of the ideal Luenberger indicator for all years (table 6).

More differentiated are the distributions of the quality aggregators when computed with reference to a **weakly disposable technology** (figure 12B). The distribution of the regular indicator is much flatter and thicker than the others, especially in 1994, when one can notice very significant differences by looking at the kernel approximations. In 1994 and 1995, in addition, the mode of the ideal distribution appears to be to the right of the average distribution. The results of the KS test show that with weak disposability the distributions are in fact different: both the ideal and average Luenberger distributions are different from the Luenberger regular distribution. In addition, the average Luenberger indicator distribution is different from that of the ideal one for 1994 and 1996.

The comparison of the distributions across technologies, i.e., strong disposability vs weak disposability of outputs, shows that the Luenberger regular and the Luenberger ideal indicators with SDO are different from those computed with a WDO technology for all the years considered. On the other hand, for the Luenberger average indicators, their distributions are different when using different disposability properties of the technology only in 1995. In 1994 and 1996, using a strong or weak disposable technology does not lead to different distributions for the quality indicator with average direction.

[Insert Figures 12A and 12B]

To summarize, the results of the quality productivity measures reinforce the results found for Chardonnay. Using an output strongly disposable technology leads to rather similar results, but referring to the presumably true technology, with weak disposable outputs, leads to quite different results. Going from a strong to a weak disposability specification of the technology increases aggregate quality scores consistently for radial and ideal indicators, while it mixes them up for the Luenberger average indicator.

6.2.3. The Quality-Quantity Trade off

Considering the relationships among the major quality attributes in Merlot, let us start with the output transformation curves between **yields** and **sugar content**. Notice that there are major differences in production between 1996, the most productive year in terms of yields, and 1994 and 1995 (figure 13). Compared to Chardonnay, apart from 1994, a particularly bad year for Merlot, the red variety results more productive than the white one (figure 14). As in Chardonnay, if we compare between disposability different specification of the technology, it appears that yields are weakly disposable with respect to sugar content, even though over a relatively short production span, i.e., up to around 13 t/ha in 1994 and 1996 but only to 9 t/ha in 1995 (figure 16). Indeed, the production level at which yields and sugar are substitutes, i.e., high production begins to be at the expenses of lower sugar content and the isoquant is negatively sloped, varies with the years. In 1994 it is at around 14 t/ha, and similarly in 1995, while in 1996 it is only at about 20 t/ha. As can be seen from the output sets, in 1996 production was much higher and apparently only partially at the expense of sugar production. Indeed, the decrease from 22 to 19° Brix is at about 23 t/ha in 1994 but only at around 36 t/ha in 1996. Also notice that Merlot results more productive than Chardonnay both in terms of yields and sugar content, i.e., Merlot output sets include those of the white variety, for 1995 and 1996, while it is not unambiguously so in 1994 (figure 14).

Interesting is also the relationship between **total acidity** and **yields**. Again, 1994 is the worst year, i.e., its output set is included in those of the other years, while 1995 and 1996 are good for acidity and yields respectively (figure 17). Also notice that the output sets appear lower for Merlot than Chardonnay in all the years, showing thus a lower potential for acidity than the white variety (figure 18). Regarding the different specifications of the technology, it appears that over a limited production span, up to 12-15 t/ha, yields are weak disposable with respect to total acidity for all the years. Notice that the substitutability, i.e., a negatively sloped isoquant, between acidity and yields thus starts at around 15 t/ha for all the years considered (figure 20).

We also look at the output isoquants for **acidity** and **sugar**. 1995 is the best year for Merlot for both quality attributes; however, there is relatively little variability in the frontiers for sugar production, while there is more variability across years for total acidity (figure 21). Again, Chardonnay is unambiguously more productive in terms of acidity, i.e., it has higher frontiers, while Merlot in terms of sugar, i.e., the frontiers are located more on the right (figure 22). Comparing different output disposability properties, it appears that the output transformation curves with weak and strong disposability of outputs seem to coincide, apart from a limited sugar content range over which acidity appears weakly disposable with respect to sugar (figure 24).

Considering **potassium** and **yields**, as in Chardonnay, notice that there are limited differences across years (figure 25). In 1996, however, the frontier is the farthest to the right and the highest, i.e., more yields and more potassium. Considering a weak disposable technology, the comparison of the output isoquants shows that for the three years considered the yields appear complement in production, i.e., weakly disposable, to potassium content (figure 28).

As already seen for Chardonnay, the output isoquants regarding **sugar** and **potassium content** for different years and between cultivars appear relatively bunched together (figure 29 and 30). In addition, in 1995 it appears that both sugar and potassium are weakly disposable, while in 1994 and 1996 only potassium appears weakly disposable to sugar content even though over a limited span of sugar content (figure 32).

We test whether quantity is a substitute with **aggregate quality**, i.e., whether there is a trade-off between quantity and aggregate quality for Merlot as well, and we look at the relationship between the Luenberger indicators and the yields (figure 36). The relationship however is not so clear, at least for 1994, when the indicators are very dispersed, especially at lower production levels, and in 1995. Only in 1996, when the production level increases the quality indicators, the regular, average and ideal, appear to decrease. These non-monotonic trends are confirmed when comparing the average values of the indicators at different production levels (table 7A). When going from 0-10 to 10-20 t/ha indeed all indicators decrease only in 1996, while in 1994 and 1995 they increase. However, when increasing the production levels above 20 t/ha, then for all the years and all the indicators their values decrease, showing the expected trade-off between quantity and aggregate quality.

[Insert Figure 36 and table 7A about here]

As an additional test of the trade-off between quantity and aggregate quality, we also compute the quality aggregator of eq. (4.14) plotting it against production level (figure 37). As already seen for Chardonnay, the three different measures - the directional regular, average and ideal distance functions - give similar results. In addition, for the three years considered there is a non-linear trade-off between the production level and aggregate quality (figure 35). Again, the bigger decrease in the aggregate quality is for production levels below 10 t/ha: the quality aggregator shifts from values above 4-5 to around 2-2.5 (figure 35 and 37). Notice also that for very low production levels, i.e., below 5 t/ha, there are extremely high values of the quality aggregator, above 20 in 1995, even though there are only few observations with those extreme values.

An additional decrease of aggregate quality is in the 10-20 t/ha production range, in which the quality aggregator decreases from 2.87-4.73 to 1.12-1.36 (table 7B). For production levels at or above 30 t/ha, the quality aggregator tends to reach the minimum of 1, even though the production levels at which this happens are higher than in Chardonnay. In 1996, a very good year for Merlot yields, the minimum is reached for production levels well above 30 t/ha. For all the production levels, 1996 shows higher values of the quality aggregator.

[Insert Figure 37 and table 7B about here]

At the production level corresponding to the yield ceiling for Appellation wines, the quality aggregator is in the range between 1.74 and 2.03, with the higher value in 1996. Compared to the production levels above 30 t/ha, overall quality is almost double at the ceiling. On the other hand, compared to production levels of 0-10 t/ha, aggregate quality decreases by about 39-57%, with again a great variation across years, but more than with Chardonnay.

7. Concluding remarks

Quality is an important dimension in many industries and vertical relationships: being able to produce what downstream firms and consumers prefer is a necessary condition for competing in the marketplace. In this study we present a systematic analysis of the relationships among different quality attributes and production levels using some of the recent developments of production economics. Looking at the output disposability properties, we are able to characterize the technology of two common grapes variety, Chardonnay and Merlot. We can observe which attribute is substitute with others and with production levels, and which is complement in production. The information can then be used to consider different practices to improve production on those aspects that are more sought after by the industry.

In addition, since it is becoming important to assess intermediate products in terms of their quality attributes content, we present a methodology to evaluate the relative performance of firms in producing these quality attributes. We compare three different measures of aggregate quality, all based on directional distance functions. One is chosen to be easily comparable to the Malmquist-type quality index based on radial distance functions. The other two measures, on the other hand, have a different direction vector and represent the major contribution of this study in the relevant literature.

The directional distance functions, a generalization of the radial distance function, have the advantage of allowing the researcher to compare firms in a preassigned direction. Thus we can compute an indicator setting the direction vector equal to the average of the group, resembling the idea of yardstick competition within the group of firms under consideration. For the other measure we consider a direction which is the ideal composition of the intermediate good, i.e., the direction vector is set equal to the ideal composition of the grapes, thus measuring firm's quality production in reference to what is the best possible composition for the intermediate product under consideration.

In grapes for wine production, sugar content is important but it is not the only quality attribute deemed relevant. It is still standard practice to remunerate firms' production with pricing schemes that consider explicitly sugar content, but the industry is also trying to find more sophisticated mechanisms to consider other quality attributes as well. Compared to the actual practice in the Italian wine industry of using only sugar content to adjust pricing for grapes, the three measures introduced in the paper allow to take into account more of the quality components important for the wine industry. For the dataset at hand, the three measures give rather different results in terms of average results for the group and dispersion of firms around the mean. In addition, we show that there are significant differences among the three distributions using alternative specifications of the technology, thus emphasizing that the investigation of the appropriate technology specification should precede the computations of the quality productivity measures.

In the paper we are also able to test whether higher production per hectare may be detrimental to specific quality aspects or to aggregate quality. The paper shows that indeed there is a trade-off between quantity and aggregate quality, which is more significant for Chardonnay compared to Merlot. In addition, both sugar and total acidity appear substitute with yields when production is above certain levels, which however vary according to the years, presumably due to different weather conditions. Moreover, this substitutability generally starts at lower production levels in Chardonnay compared to Merlot, which thus appears a less productive variety. According to the evidence presented, it appears that the use of quantity ceilings that many self-regulating groups in Europe are implementing for agricultural commodities may contribute to improve aggregate quality. Further research however should investigate at which production level to tune the production process to have the efficient level of quality attributes, considering also that the trade offs change across the years considered.

The paper can be improved along different dimensions. A possible extension, more geared towards industry applications, would be to investigate how one can create incentives for the production of the right quality attributes given the information about the technology. This is an important topic, which may be of interest to suppliers, buyers, cooperatives, retailers, etc. How to compensate producers for their efforts and how to give the right signal on the more valuable attributes is indeed prone to increase the efficiency of supply chain relationships and of food industries in particular.

In this study we have employed a rich dataset of quality attributes, thus using information that may not be cheaply available in everyday industry practice. Exploiting the properties of the technology and other appropriate methodologies, it may be useful for industry applications to investigate whether the use of a more limited set of variables may still provide sufficient information to give useful signals to producers. Moreover, the aggregate quality measures presented in the paper needs to be compared with the single measures of quality that are more commonly employed for evaluating the quality of raw commodities.

To conclude, it is worth reminding that the various measures may generate pricing mechanisms with different incentive power and have different impacts in terms of efficiency and inequality of revenues earned by participating firms. Indeed, a more powerful incentive measure may increase efficiency but may also cause greater inequality among producers. Greater inequality is often not valuable in some cooperatives or in other producer groups where equality of treatment may be preferred, even if this may imply lower rewards for quality.

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Table 1-A. Inputs and Outputs - CHARDONNAY

		1994	n=214			**1995**	n=187			**1996**	n=213		
Variable	Unit meas.	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max
Altimetry	mt	268.7	97.2	170.0	500.0	259.0	90.0	180.0	500.0	260.0	91.0	180.0	500.0
Vines per hectare	no	3199.0	776.0	1500.0	5000.0	3194.0	788.0	1500.0	5000.0	3176.0	776.0	1500.0	5000.0
Buds per branch	no	23.0	7.0	10.0	41.0	27.0	9.0	9.0	62.0	31.0	11.0	8.0	89.0
Roots depth°	1-3	2.4	0.9	1.0	3.0	2.3	0.9	1.0	3.0	2.4	0.9	1.0	3.0
Water holding capacity°	1-4	2.3	1.0	1.0	4.0	2.2	1.0	1.0	4.0	2.3	1.0	1.0	4.0
Total calcium°	1-5	3.4	1.2	1.0	5.0	3.4	1.2	1.0	5.0	3.4	1.1	1.0	5.0
Mean humidity*	%	58.0	-	-	-	62.0	-	-	-	67.4	-	-	-
Mean temperature*	°C	22.6	-	-	-	20.1	-	-	-	19.7	-	-	-
Rainfall**	mm	172.2	-	-	-	61.7	-	-	-	124.6	-	-	-
Radiation**	cal/sqcm	14045.0	-	-	-	11824.0	-	-	-	10927.0	-	-	-
Sun hours**	no	321.7	-	-	-	266.4	-	-	-	253.7	-	-	-
Temperature excursion**	°C	593.4	-	-	-	534.3	-	-	-	509.9	-	-	-
Sugar content	°Brix	19.9	1.4	15.7	25.4	19.6	1.4	13.2	22.8	19.2	1.0	16.2	21.7
Total acidity	gr/lt	8.7	1.7	5.6	16.1	10.6	1.8	6.7	15.5	11.9	1.2	8.4	17.0
pH	1-14	3.2	0.1	2.8	3.7	3.2	0.1	2.8	3.4	3.2	0.1	2.9	3.6
Tartaric acidity	gr/lt	6.5	0.8	3.6	8.9	7.9	0.8	5.9	10.0	7.1	0.6	5.6	9.0
Malic acidity	gr/lt	3.9	1.5	0.8	9.5	5.6	1.5	2.6	10.0	5.7	1.1	3.3	8.1
Potassium content	gr/lt	1.5	0.2	0.8	2.3	1.6	0.2	1.2	2.3	1.7	0.2	1.2	2.0
Grapes production per hectare	0.1 t/ha	144.7	58.5	32.0	356.7	134.0	56.8	14.8	362.0	182.0	73.4	40.0	451.0

° Categorical variable

* Average conditions for the last 40 days before harvest

** Summation for the last 40 days before harvest

Table 1-B. Inputs and Outputs - MERLOT

		1994	n=78			**1995**	n=127			**1996**	n=120		
Variable	Unit meas.	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max	Mean	St. dev.	Min	Max
Altimetry	mt	210.0	65.7	180.0	450.0	203.7	53.7	180.0	450.0	203.3	54.8	180.0	450.0
Vines per hectare	no	2748.0	704.0	1500.0	4100.0	2681.5	627.8	1800.0	4100.0	2650.0	618.9	1800.0	4100.0
Buds per branch	no	29.8	8.5	7.0	58.0	28.9	9.6	12.0	61.0	37.6	14.4	16.0	97.0
Roots depth°	1-3	2.3	0.9	1.0	3.0	2.5	0.8	1.0	3.0	2.5	0.8	1.0	3.0
Water holding capacity°	1-4	2.4	1.2	1.0	4.0	2.7	1.1	1.0	4.0	2.8	1.1	1.0	4.0
Total calcium°	1-5	3.3	1.4	1.0	5.0	3.5	1.2	1.0	5.0	3.4	1.3	1.0	5.0
Mean humidity*	%	63.0	-	-	-	68.5	-	-	-	65.5	-	-	-
Mean temperature*	°C	20.7	-	-	-	17.6	-	-	-	17.1	-	-	-
Rainfall**	mm	274.9	-	-	-	89.2	-	-	-	83.0	-	-	-
Radiation**	cal/sqcm	12349.0	-	-	-	9439.0	-	-	-	9470.0	-	-	-
Sun hours**	no	281.7	-	-	-	214.9	-	-	-	220.0	-	-	-
Temperature excursion**	°C	549.2	-	-	-	477.0	-	-	-	504.9	-	-	-
Sugar content	°Brix	20.2	1.4	17.0	24.6	20.5	1.7	13.5	23.9	19.8	1.3	16.3	22.5
Total acidity	gr/lt	6.4	1.6	4.3	11.9	9.6	2.5	5.0	17.7	8.7	1.0	6.5	14.4
pH	1-14	3.6	0.2	3.1	4.0	3.4	0.1	3.1	3.9	3.5	0.5	3.2	8.4
Tartaric acidity	gr/lt	6.4	1.2	4.3	9.9	7.3	0.9	3.7	9.8	5.4	0.7	2.8	7.2
Malic acidity	gr/lt	2.8	1.2	1.2	6.3	3.9	1.1	1.7	8.0	3.7	0.7	2.1	6.9
Potassium content	gr/lt	1.8	0.2	1.1	2.5	1.7	0.2	1.2	2.3	1.9	0.2	1.5	2.3
Grapes production per hectare	0.1 t/ha	157.3	63.9	48.6	345.0	139.8	63.8	11.0	365.0	220.7	83.3	44.0	522.9

° Categorical variable

* Average conditions for the last 40 days before harvest

** Summation for the last 40 days before harvest

Table 2. Hyphotesis Tests for Returns to Scale

	Mann- Whitney		Kolmogorov- Smirnov	
	z	Prob > |z|*	D	Corr. P-value*
Chardonnay				
1994	-0.38	0.71	0.02	1.00
1995	-0.23	0.82	0.02	1.00
1996	-0.11	0.91	0.01	1.00
Merlot				
1994	-0.46	0.65	0.03	1.00
1995	-0.2	0.84	0.02	1.00
1996	-0.49	0.62	0.04	1.00

H_0: CRS; H_1: VRS.

*: Prob. of error in rejecting the null hypothesis that the distributions are the same.

Table 2A. Output Disposability Tests for All and Each Individual Output
(Prob. of error in rejecting the null hypothesis that the distributions are the same)

		All outputs	Sugar content	Total acidity	pH	Tartaric acidity	Malic acidity	Potassium content	Yields
Chardonnay									
1994	MW	**0.00**	0.78	0.36	0.30	**0.05**	**0.00**	**0.10**	0.46
	KS	**0.00**	1.00	0.79	0.87	0.18	**0.00**	0.27	0.99
1995	MW	**0.00**	0.24	0.13	0.52	0.30	**0.00**	**0.01**	0.38
	KS	**0.00**	0.88	0.54	0.99	0.80	**0.00**	**0.02**	0.99
1996	MW	**0.00**	0.53	**0.04**	0.25	0.32	**0.00**	**0.00**	0.80
	KS	**0.00**	1.00	0.17	0.86	0.92	**0.05**	**0.01**	1.00
Merlot									
1994	MW	**0.00**	0.34	0.65	0.65	0.61	**0.06**	**0.06**	0.63
	KS	0.35	1.00	1.00	1.00	1.00	0.88	0.88	1.00
1995	MW	**0.00**	0.83	**0.08**	0.48	0.29	**0.05**	**0.06**	0.47
	KS	**0.01**	1.00	0.29	1.00	0.95	0.22	0.29	1.00
1996	MW	**0.00**	0.66	0.14	0.51	0.58	**0.09**	0.13	0.21
	KS	**0.00**	1.00	0.64	1.00	1.00	0.64	0.76	0.34

H_0: Strong disposabiltiy of all outputs (yields and quality attributes).

H_1: Weak disposabiltiy of the indicated output(s).

MW: Mann-Whitney test for equality of distributions; KS: Kolmogorov-Smirnov test for equality of distributions.

Table 2B. (Joint) Disposability Tests of Yields and Individual Quality Attribute
(Prob. of error in rejecting the null hypothesis that the distributions are the same)

		Sugar content	Total acidity	pH	Tartaric acidity	Malic acidity	Potassium content
Chardonnay							
1994	MW	0.47	0.37	0.43	0.85	0.59	0.43
	KS	0.99	0.97	0.99	1.00	1.00	0.99
1995	MW	0.31	0.43	0.54	0.36	0.61	0.37
	KS	0.98	0.99	0.99	0.98	1.00	0.98
1996	MW	0.80	0.75	0.85	0.92	0.75	0.83
	KS	1.00	1.00	1.00	1.00	1.00	1.00
Merlot							
1994	MW	0.76	0.77	0.59	0.57	0.69	0.68
	KS	1.00	1.00	1.00	1.00	1.00	1.00
1995	MW	0.52	0.46	0.47	0.40	0.66	0.41
	KS	1.00	0.99	1.00	0.99	1.00	0.99
1996	MW	0.59	0.47	0.62	0.60	0.68	0.56
	KS	1.00	1.00	1.00	1.00	1.00	1.00

H_0: Strong disposability of all outputs but the indicated quality attribute.

H_1: Weak disposabiltiy of the indicated quality attribute and yields.

MW: Mann-Whitney test for equality of distributions; KS: Kolmogorov-Smirnov test for equality of distributions.

Table 2C. (Joint) Disposability Tests of Yields and Individual Quality Attribute
(Prob. of error in rejecting the null hypothesis that the distributions are the same)

		Sugar content	Total acidity	pH	Tartaric acidity	Malic acidity	Potassium content
Chardonnay							
1994	MW	0.79	0.29	0.26	0.13	**0.00**	**0.09**
	KS	1.00	0.79	0.87	0.54	**0.01**	0.27
1995	MW	0.18	0.14	0.69	0.27	**0.00**	**0.01**
	KS	0.72	0.54	1.00	0.72	**0.00**	**0.03**
1996	MW	0.53	**0.03**	0.28	0.40	**0.00**	**0.00**
	KS	1.00	0.22	0.92	0.97	**0.04**	**0.02**
Merlot							
1994	MW	0.44	0.80	0.61	0.55	**0.07**	**0.07**
	KS	1.00	1.00	1.00	1.00	0.96	0.96
1995	MW	0.89	**0.08**	0.47	0.23	**0.09**	**0.05**
	KS	1.00	0.37	1.00	0.88	0.46	0.29
1996	MW	0.64	**0.08**	0.50	0.57	0.11	**0.10**
	KS	1.00	0.53	1.00	**0.10**	0.75	0.64

H_0: Strong disposabiltiy of all outputs but yields.

H_1: Weak disposabiltiy of the indicated quality attribute and yields.

MW: Mann-Whitney test for equality of distributions; KS: Kolmogorov-Smirnov test for equality of distributions.

Table 2D. Results of the Joint Disposability Tests of Yields and Each Individual Quality Attribute

		Sugar content	Total acidity	pH	Tartaric acidity	Malic acidity	Potassium content
Chardonnay							
1994	MW	S	S	S	S	W^s	W^s
	KS	S	S	S	S	W^s	S
1995	MW	S	S	S	S	W^s	W^s
	KS	S	S	S	S	W^s	W^s
1996	MW	S	W^s	S	S	W^s	W^s
	KS	S	S	S	S	W^s	W^s
Merlot							
1994	MW	S	S	S	S	W^s	W^s
	KS	S	S	S	S	S	S
1995	MW	S	W^s	S	S	W^s	W^s
	KS	S	S	S	S	S	S
1996	MW	S	W^s	S	S	S	W^s
	KS	S	S	S	S	S	S

S: Strong disposability of the indicated quality attribute and yields (Y vs. S).

W^s: Weak disposability of the indicated quality attribute (Y <-- S).

Table 3A. Luenberger Quality Indicator - Regular Direction (Strong Disposability of Quality Attributes)

	No. obs.	Mean	St. dev.	Min	Max
Chardonnay					
1994	214	0.001	0.044	-0.139	0.183
1995	187	0.004	0.041	-0.202	0.106
1996	213	0.003	0.046	-0.173	0.132
Merlot					
1994	78	-0.018	0.066	-0.188	0.145
1995	127	0.007	0.035	-0.145	0.092
1996	120	0.011	0.042	-0.089	0.215

Table 3B. Luenberger Quality Indicator - Regular Direction (Weak Disposability of Quality Attributes)

	No. obs.	Mean	St. dev.	Min	Max
Chardonnay					
1994	214	0.033	0.094	-0.334	0.438
1995	187	0.046	0.101	-0.273	0.414
1996	213	0.042	0.095	-0.258	0.392
Merlot					
1994	78	0.035	0.098	-0.150	0.218
1995	127	0.046	0.090	-0.269	0.220
1996	120	0.032	0.094	-0.277	0.267

Table 4A. Luenberger Quality Indicator - Average Composition (Strong Disposability of Quality Attributes)

	No. obs.	Mean	St. dev.	Min	Max
Chardonnay					
1994	214	0.004	0.056	-0.137	0.349
1995	187	0.005	0.044	-0.216	0.130
1996	213	0.004	0.047	-0.173	0.164
Merlot					
1994	78	-0.011	0.082	-0.188	0.286
1995	127	0.008	0.037	-0.145	0.151
1996	120	0.014	0.058	-0.083	0.451

Table 4B. Luenberger Quality Indicator - Average Composition (Weak Disposability of Quality Attributes)

	No. obs.	Mean	St. dev.	Min	Max
Chardonnay					
1994	214	0.006	0.071	-0.379	0.297
1995	187	-0.002	0.071	-0.439	0.303
1996	213	0.020	0.086	-0.257	0.515
Merlot					
1994	78	-0.013	0.090	-0.215	0.352
1995	127	0.016	0.067	-0.222	0.207
1996	120	-0.001	0.070	-0.278	0.265

Table 5A. Luenberger Quality Indicator - Ideal Composition
(Strong Disposability of Quality Attributes)

	No. obs.	Mean	St. dev.	Min	Max
Chardonnay					
1994	214	0.006	0.091	-0.292	0.636
1995	187	0.000	0.085	-0.559	0.217
1996	213	-0.003	0.079	-0.503	0.238
Merlot					
1994	78	-0.018	0.181	-0.517	0.739
1995	127	0.005	0.088	-0.581	0.494
1996	120	0.011	0.108	-0.306	0.869

Table 5B. Luenberger Quality Indicator - Ideal Composition
(Weak Disposability of Quality Attributes)

	No. obs.	Mean	St. dev.	Min	Max
Chardonnay					
1994	214	0.017	0.069	-0.145	0.283
1995	187	0.000	0.073	-0.479	0.263
1996	213	0.021	0.066	-0.171	0.286
Merlot					
1994	78	-0.003	0.053	-0.133	0.127
1995	127	0.014	0.064	-0.177	0.148
1996	120	0.020	0.054	-0.136	0.222

Table 6: Are the two distributions different?
(Prob. of error in rejecting the null hypothesis that the distributions are the same)

	Average (SDO) vs. Regular (SDO)	Ideal (SDO) vs. Regular (SDO)	Average (SDO) vs. Ideal (SDO)	Average (WDO) vs. Regular (WDO)	Ideal (WDO) vs. Regular (WDO)	Average (WDO) vs. Ideal (WDO)	Regular (SDO) vs. Regular (WDO)	Average (SDO) vs. Average (WDO)	Ideal (SDO) vs. Ideal (WDO)
	Probability	Probability	Probability	Probability	Probability	Probability	Probability	Probability	Probability
Chardonnay									
1994	1.000	0.998	0.966	**0.003**	**0.023**	0.626	**0.000**	**0.017**	**0.002**
1995	1.000	0.976	0.976	**0.000**	**0.000**	0.717	**0.000**	0.307	0.123
1996	1.000	0.965	0.924	**0.003**	**0.003**	0.924	**0.000**	**0.006**	**0.006**
Merlot									
1994	1.000	0.611	0.611	**0.007**	**0.000**	**0.082**	**0.000**	0.611	**0.053**
1995	1.000	0.881	0.986	**0.003**	**0.000**	0.786	**0.000**	**0.022**	**0.015**
1996	1.000	0.858	0.936	**0.000**	**0.005**	**0.005**	**0.000**	0.193	**0.025**

Regular: $\mathbf{g_s} = \mathbf{s}$;

Average: $\mathbf{g_s} = \text{mean}(\mathbf{s})$;

Ideal: $\mathbf{g_s} = \text{ideal}(\mathbf{s})$.

Table 7A. Average values of Quality Indicators, based on directional distance fn, at different production levels

	Dir. Regular			Dir. Average			Dir. Ideal		
	0-10 t	10-20 t	> 20 t	0-10 t	10-20 t	> 20 t	0-10 t	10-20 t	> 20 t
Chardonnay									
1994	0.0212	0.0000	-0.0191	0.0278	0.0019	-0.0181	0.0354	0.0032	-0.0235
1995	0.0064	0.0060	-0.0305	0.0086	0.0080	-0.0169	0.0077	0.0083	-0.0222
1996	0.0243	0.0095	-0.0192	0.0290	0.0111	-0.0149	0.0350	0.0111	-0.0373
Merlot									
1994	-0.0203	-0.0081	-0.0620	-0.0105	0.0039	-0.0414	-0.0148	-0.0028	-0.0515
1995	0.0105	0.0144	-0.0254	0.0125	0.0176	-0.0212	0.0065	0.0276	-0.0535
1996	0.0530	0.0192	-0.0013	0.0877	0.0240	0.0006	0.0928	0.0345	-0.0122

Table 7B. Average values of Aggregate Quality (1/S(s), based on directional distance function (regular direction), at different production levels

	0-10 t	14 t	10-20 t	20-30 t	> 20 t	> 30 t
Chardonnay						
1994	3.24	1.73	1.76	1.19	1.18	1.03
1995	3.41	1.61	1.63	1.15	1.14	1.00
1996	3.50	2.00	1.88	1.27	1.23	1.05
Merlot						
1994	2.87	1.75	1.56	1.12	1.11	1.04
1995	3.85	1.74	1.76	1.16	1.15	1.00
1996	4.73	2.03	1.87	1.36	1.31	1.14

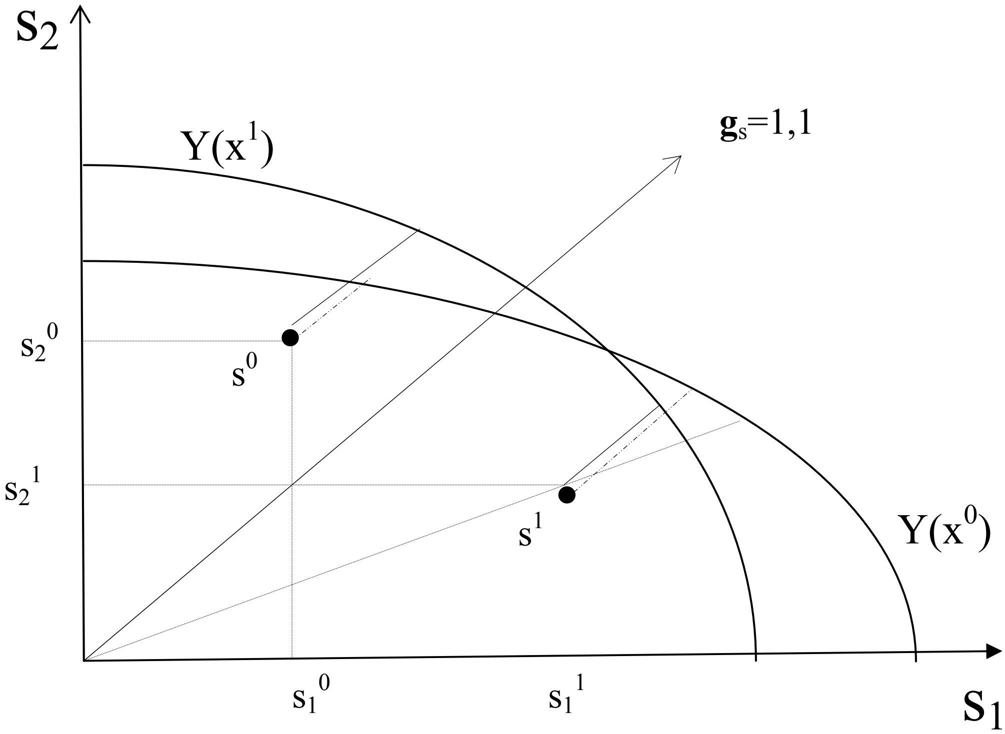


Figure 1. Directional distance function

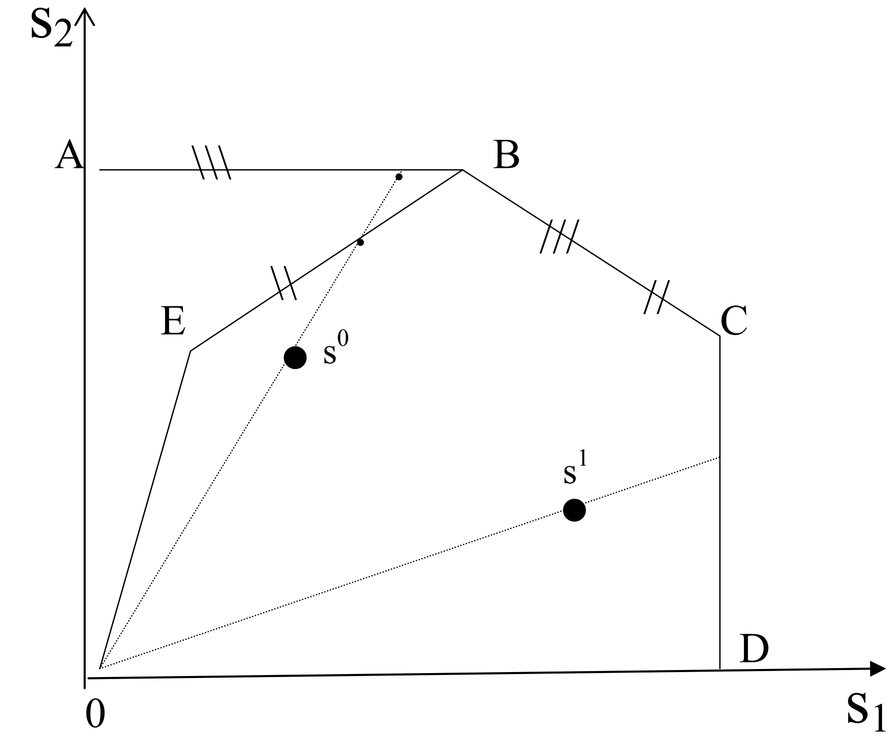


Figure 2. Strong and Weak Output Disposability

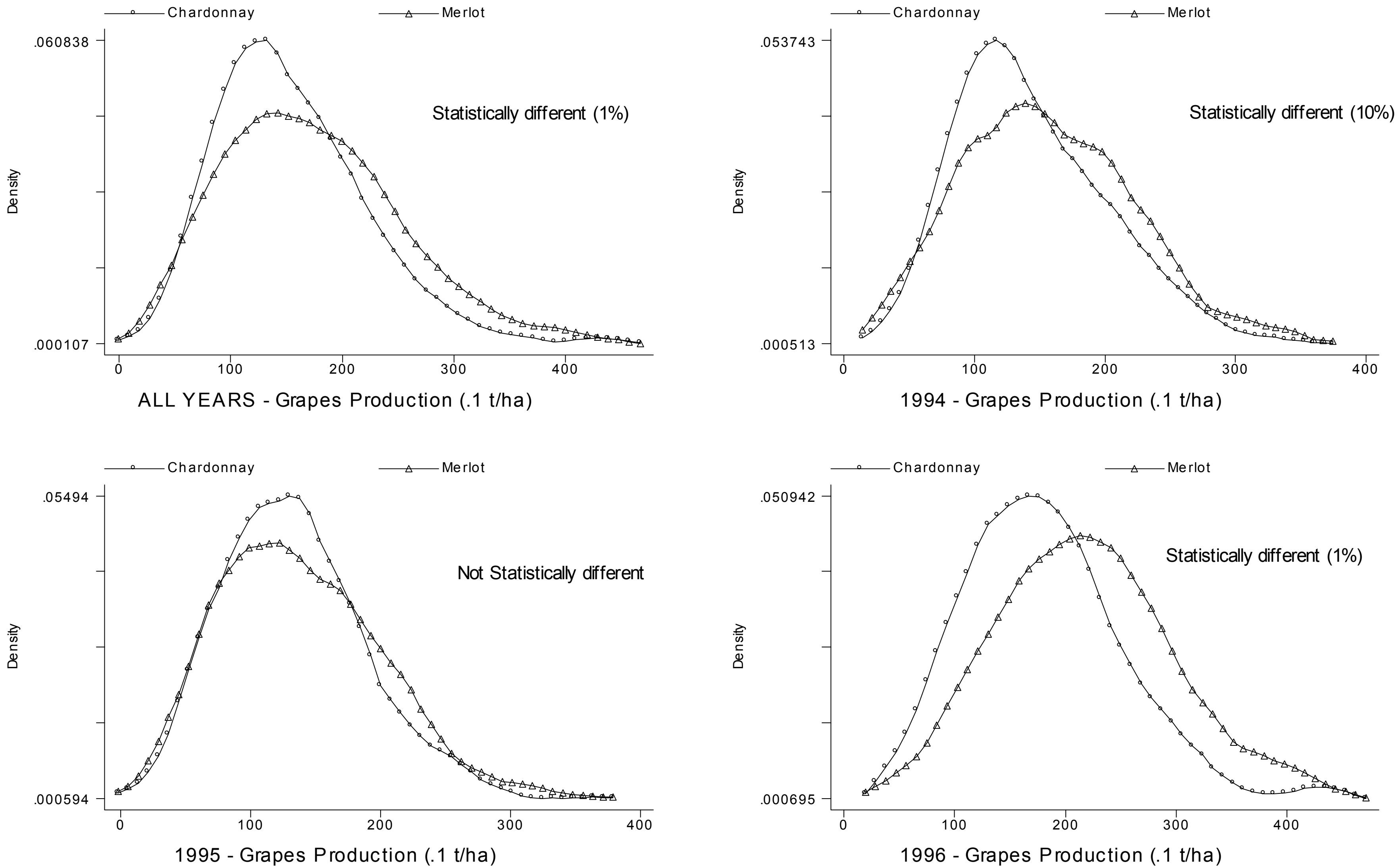


Figure 3. Grapes production per hectare in different years

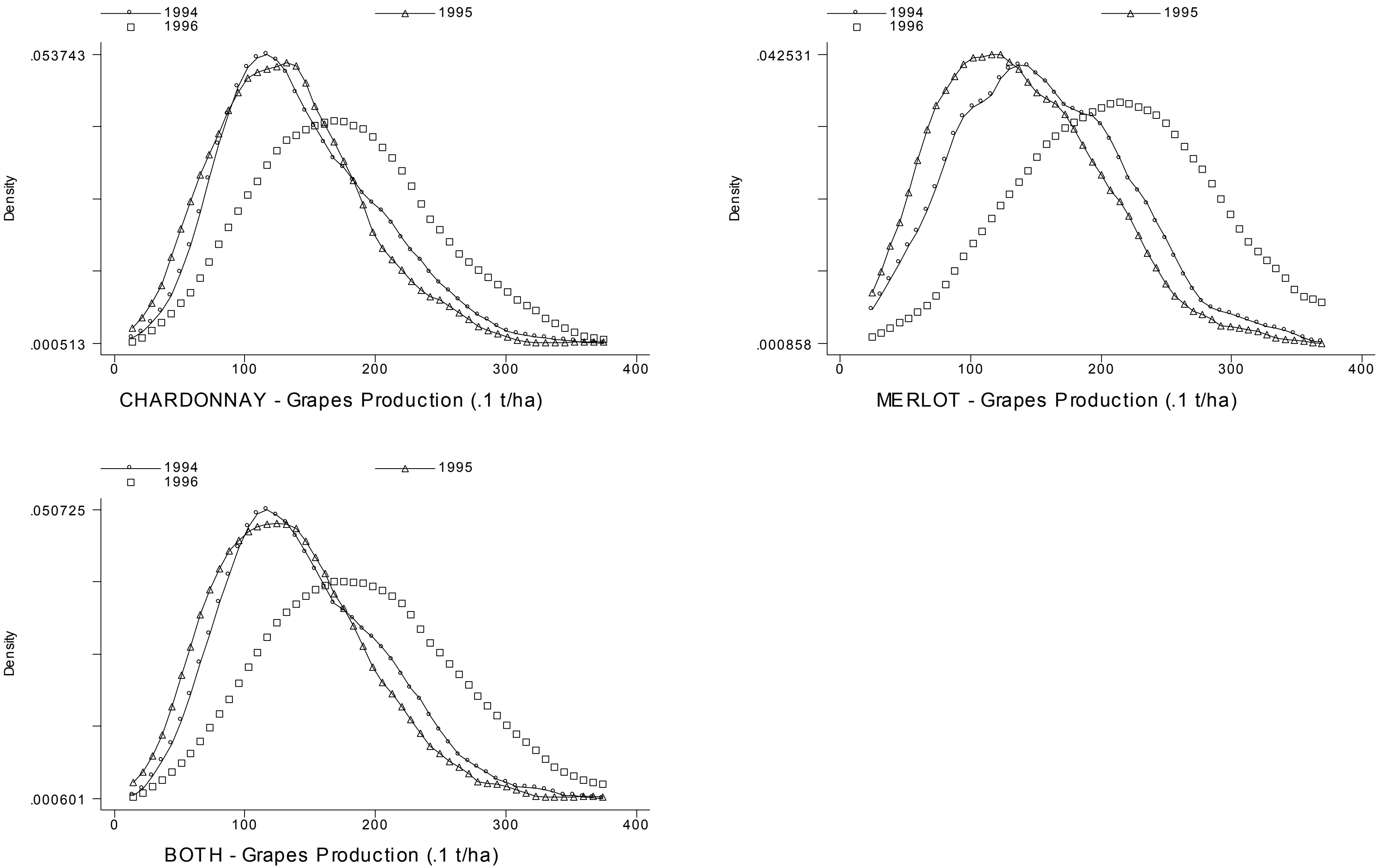


Figure 4. Grapes production per hectare

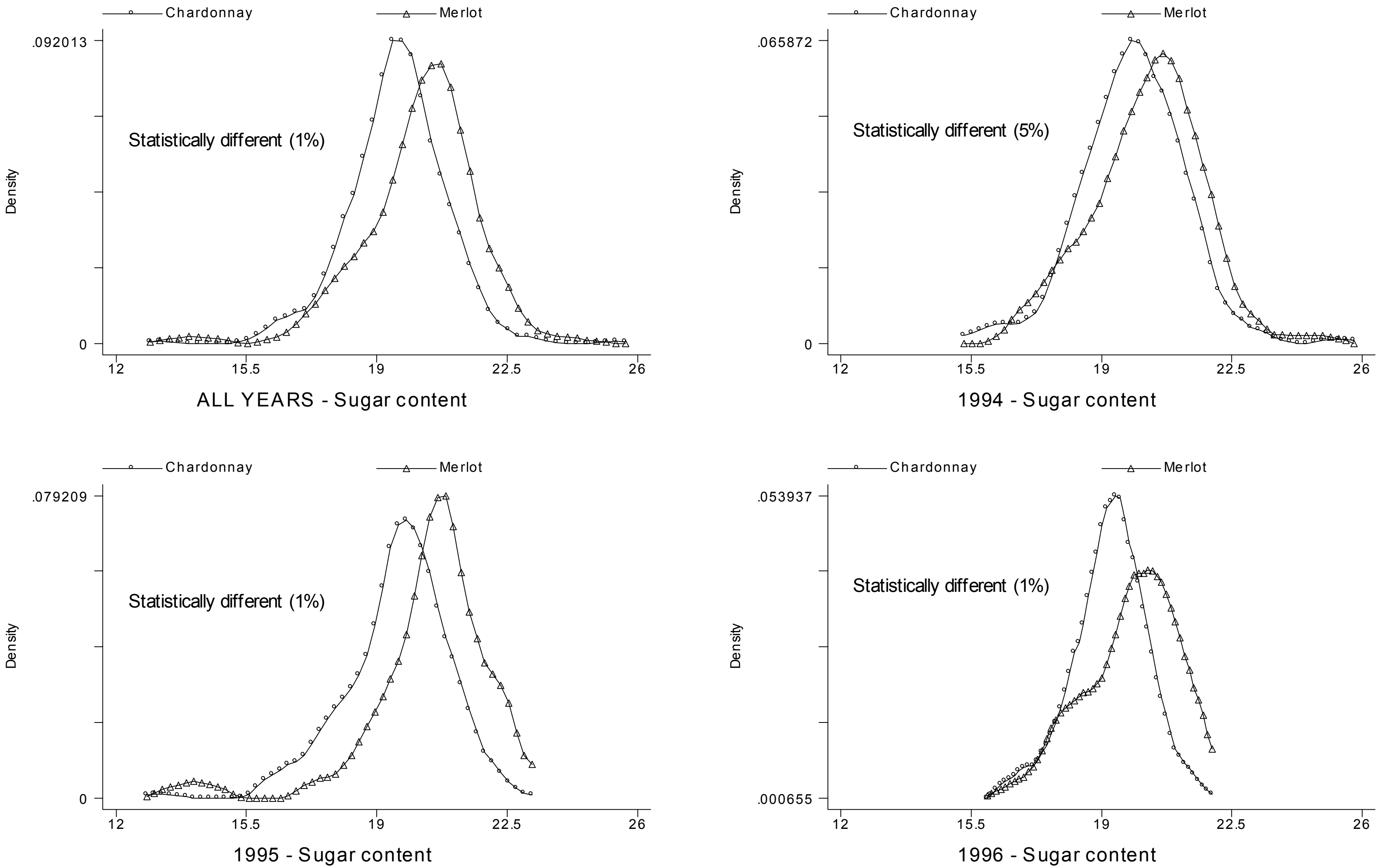


Figure 5. Sugar content in different years

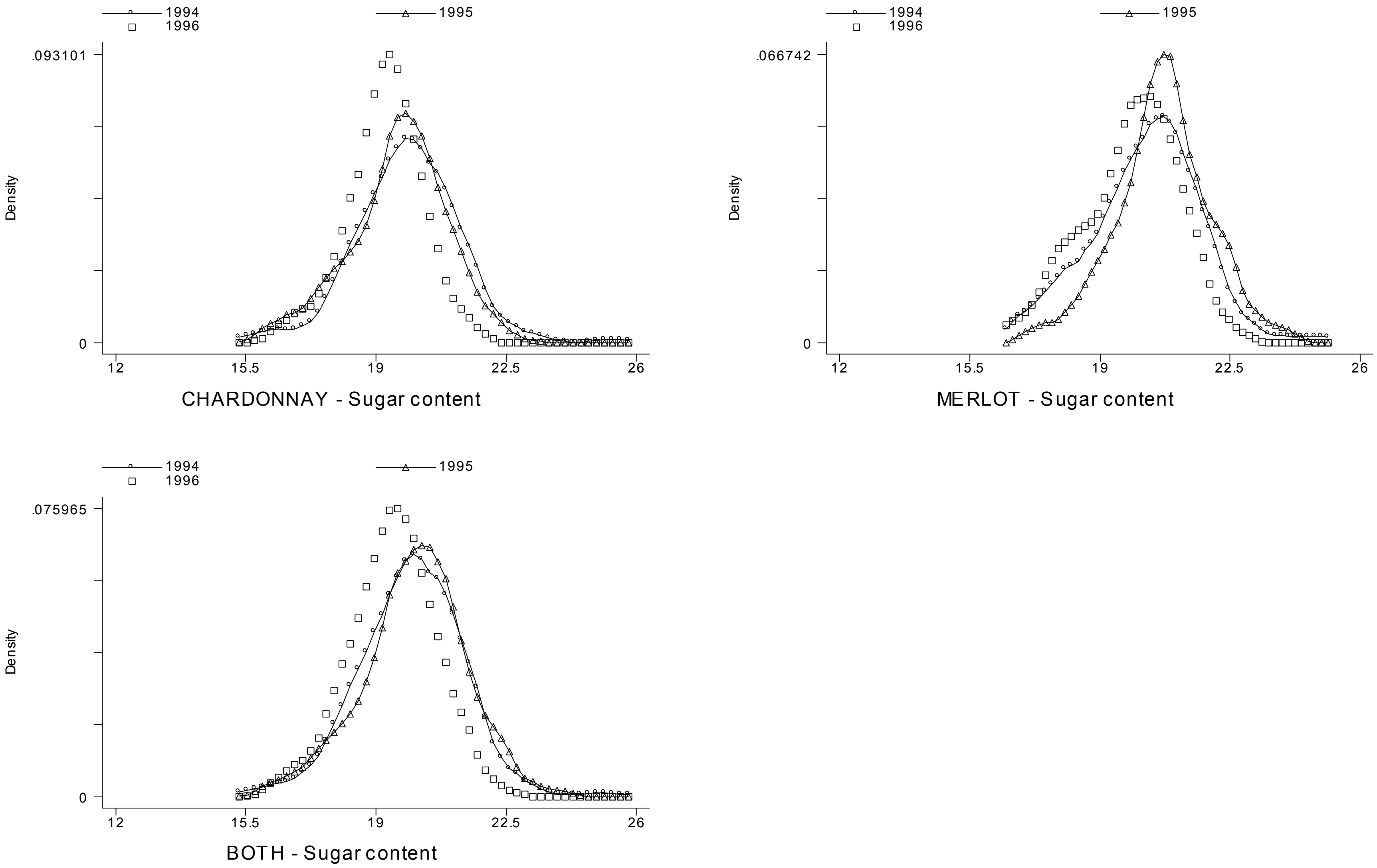


Figure 6. Sugar content

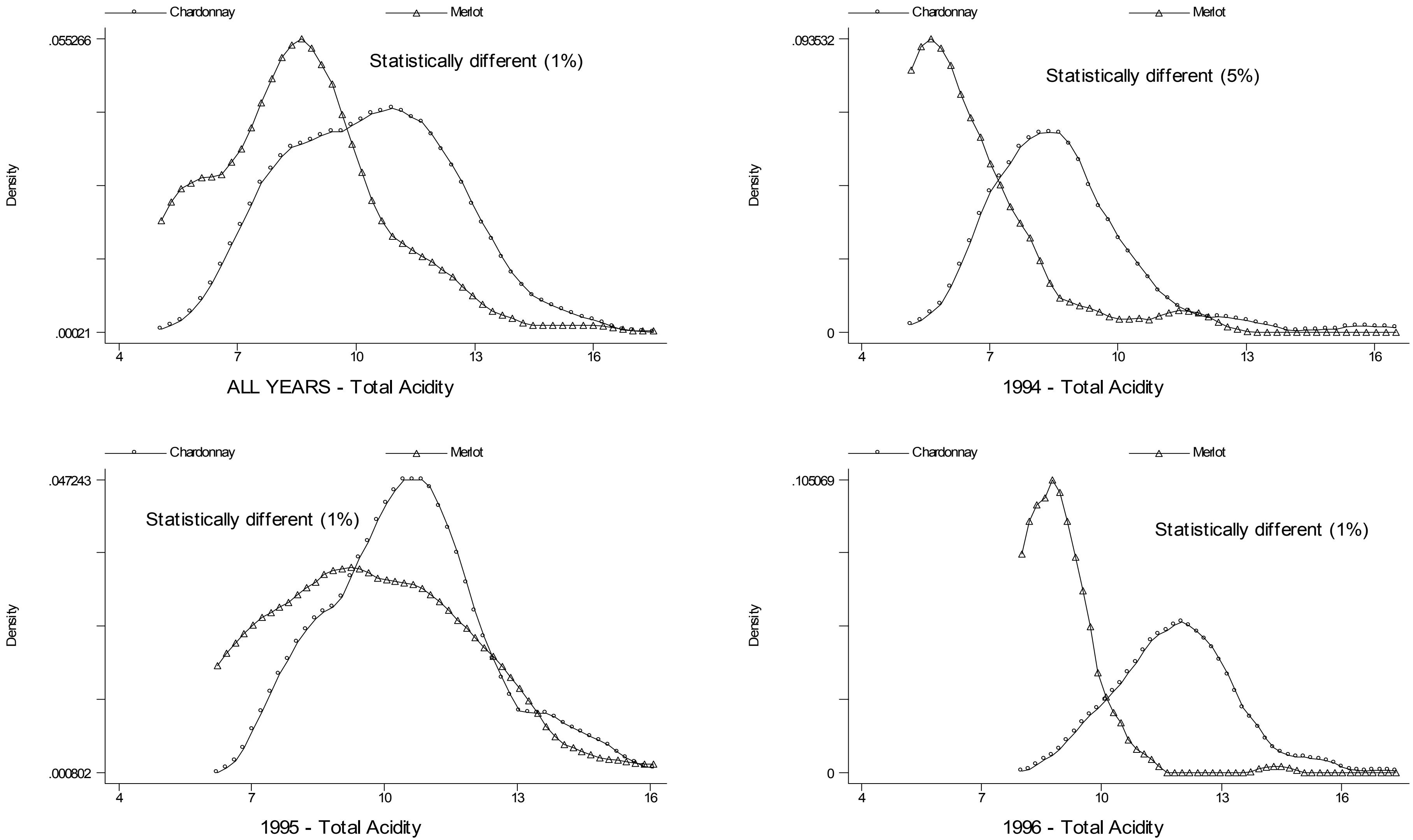


Figure 7. Total Acidity in different years

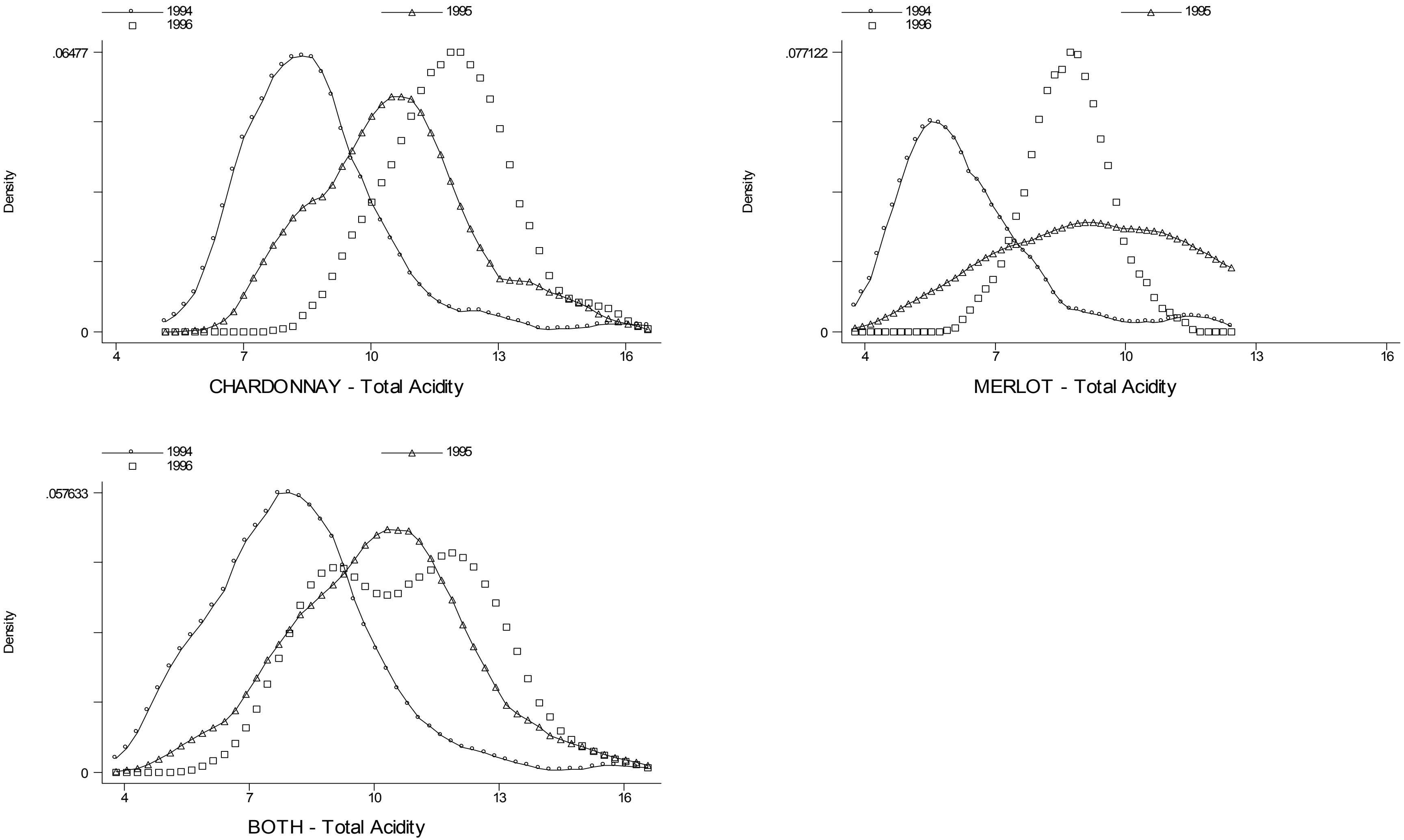


Figure 8. Total Acidity

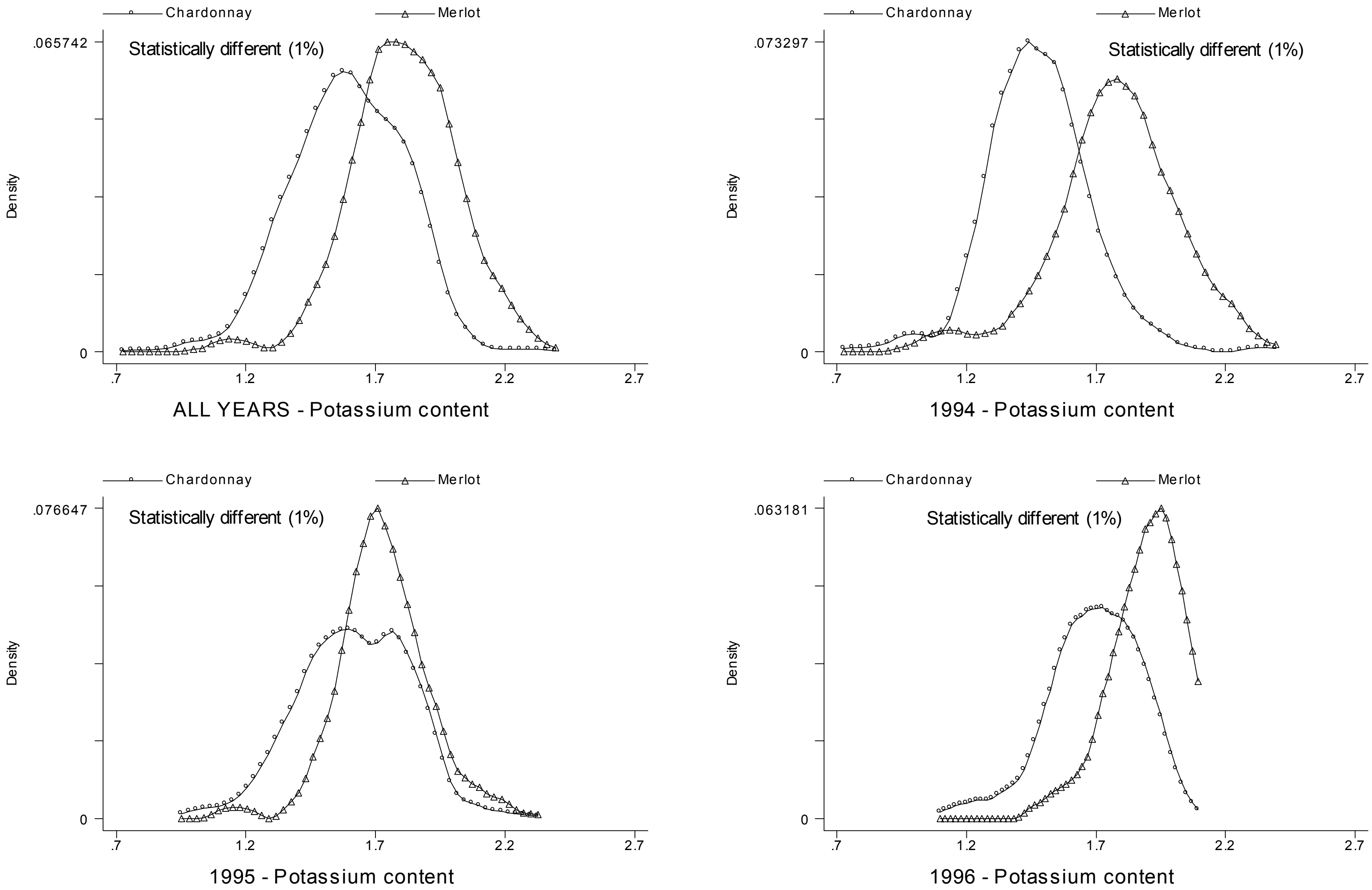


Figure 9. Potassium content in different years

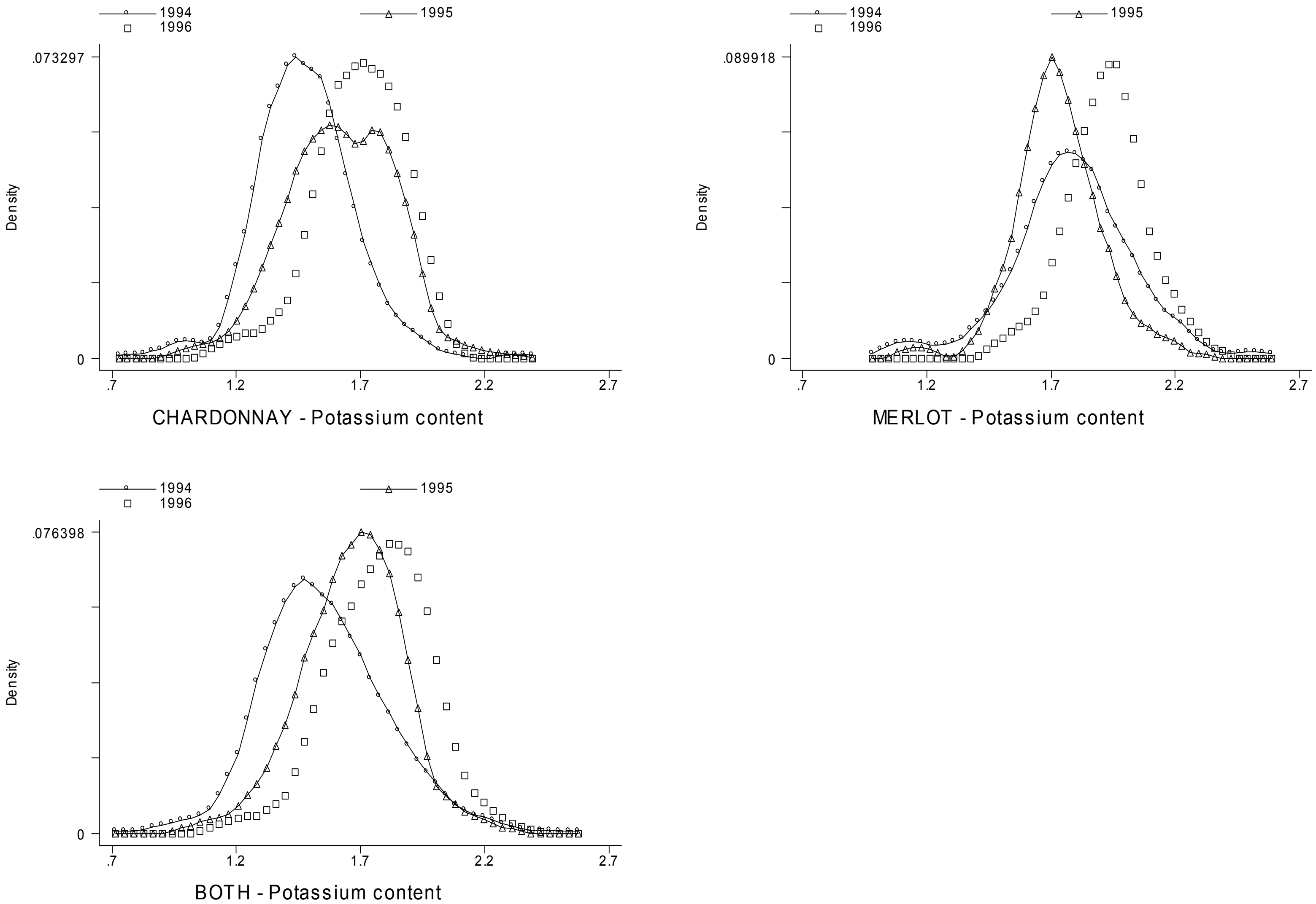


Figure 10. Potassium content

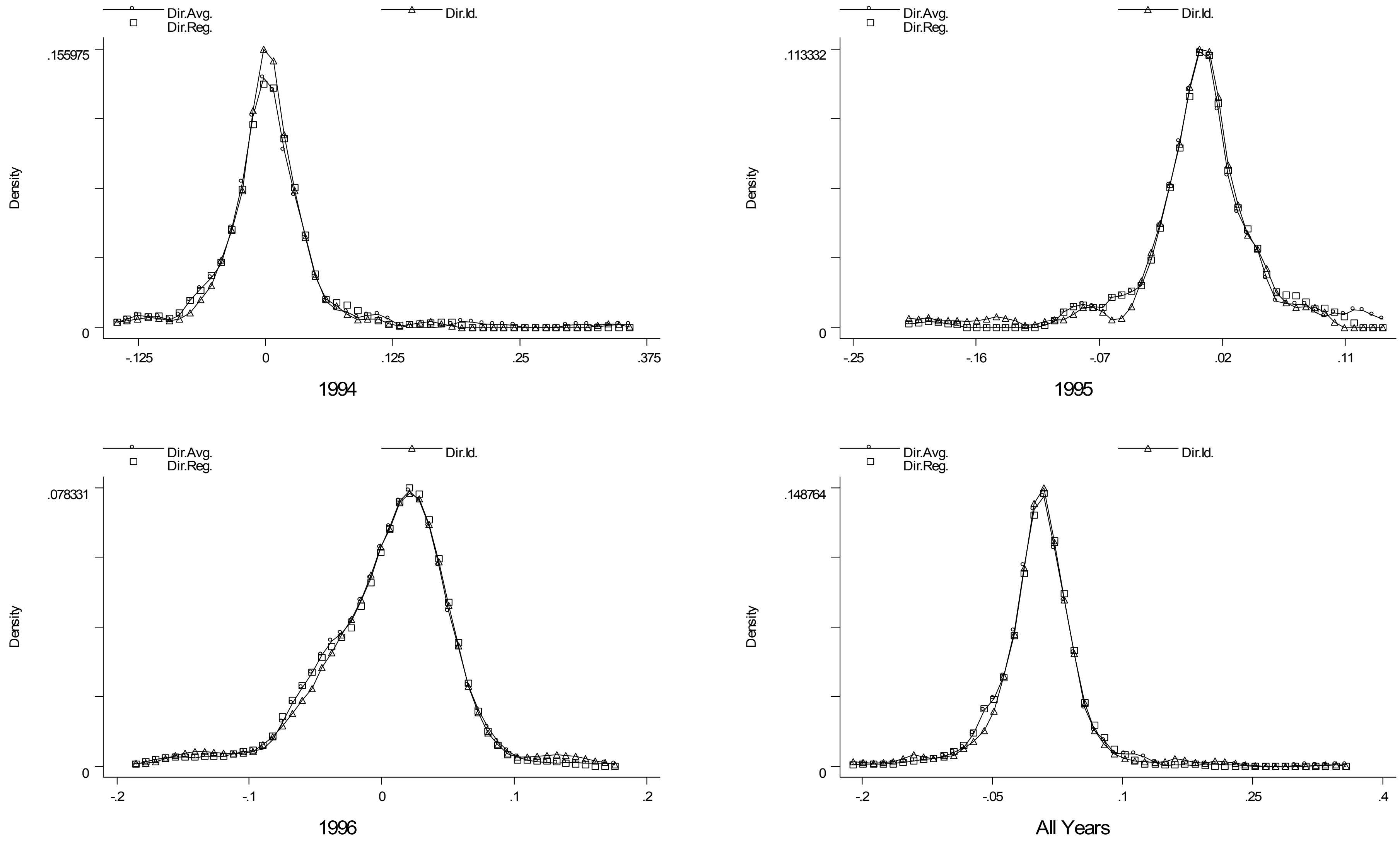


Figure 11A. Luenberg Quality Indicators - SDO
CHARDONNAY

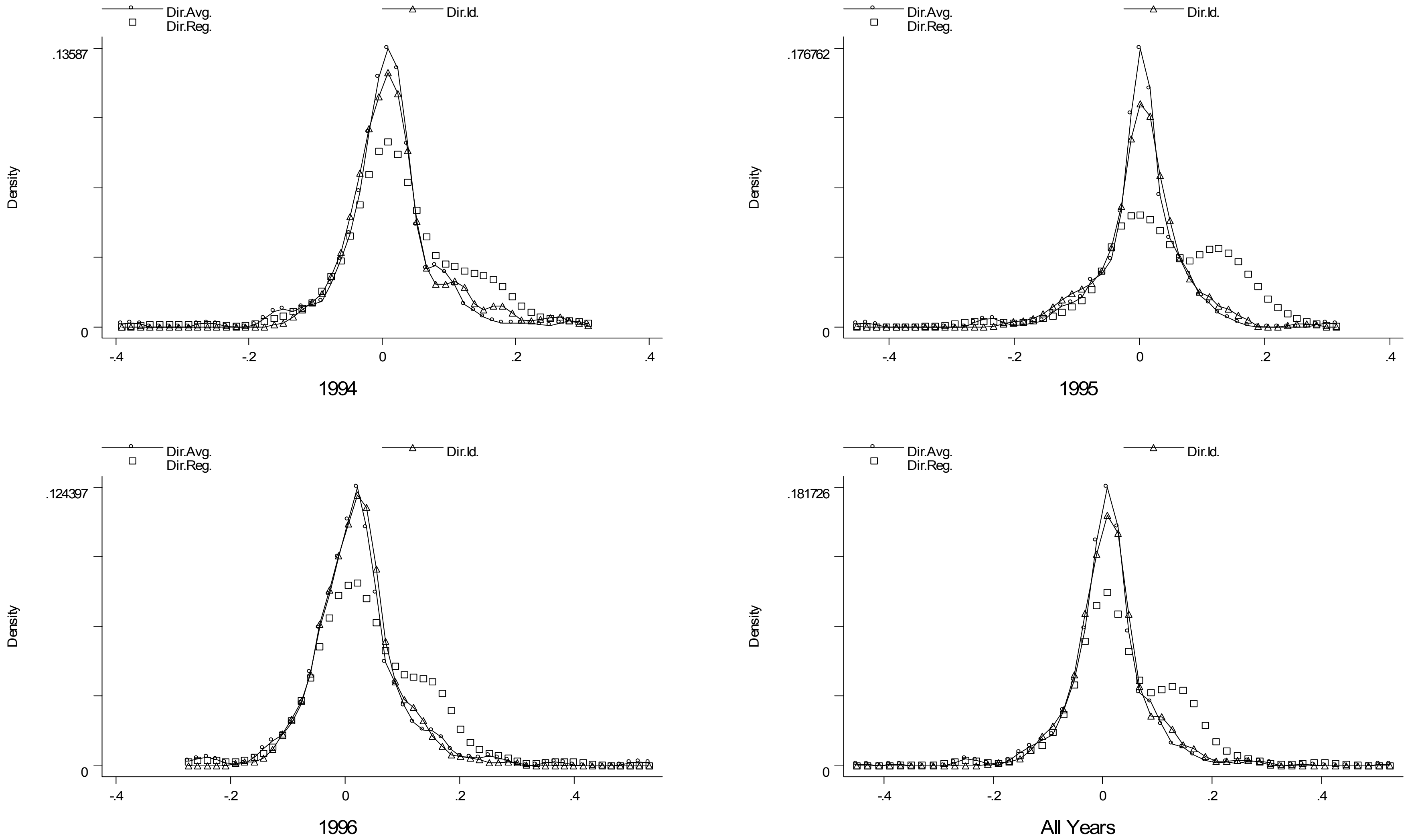


Figure 11B. Luenberg Quality Indicators – WDO CHARDONNAY

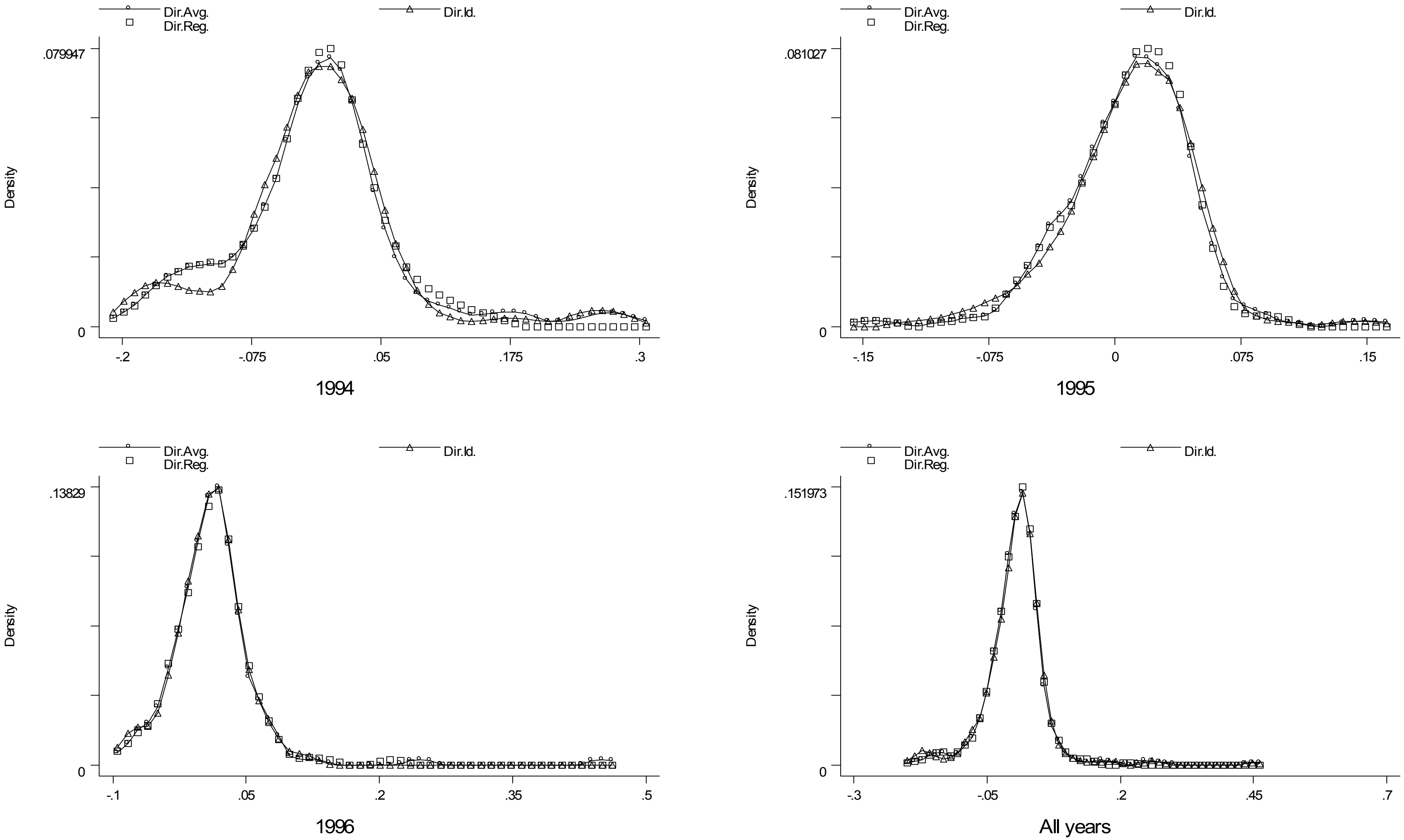


Figure 12A. Luenberg Quality Indicators – SDO
MERLOT

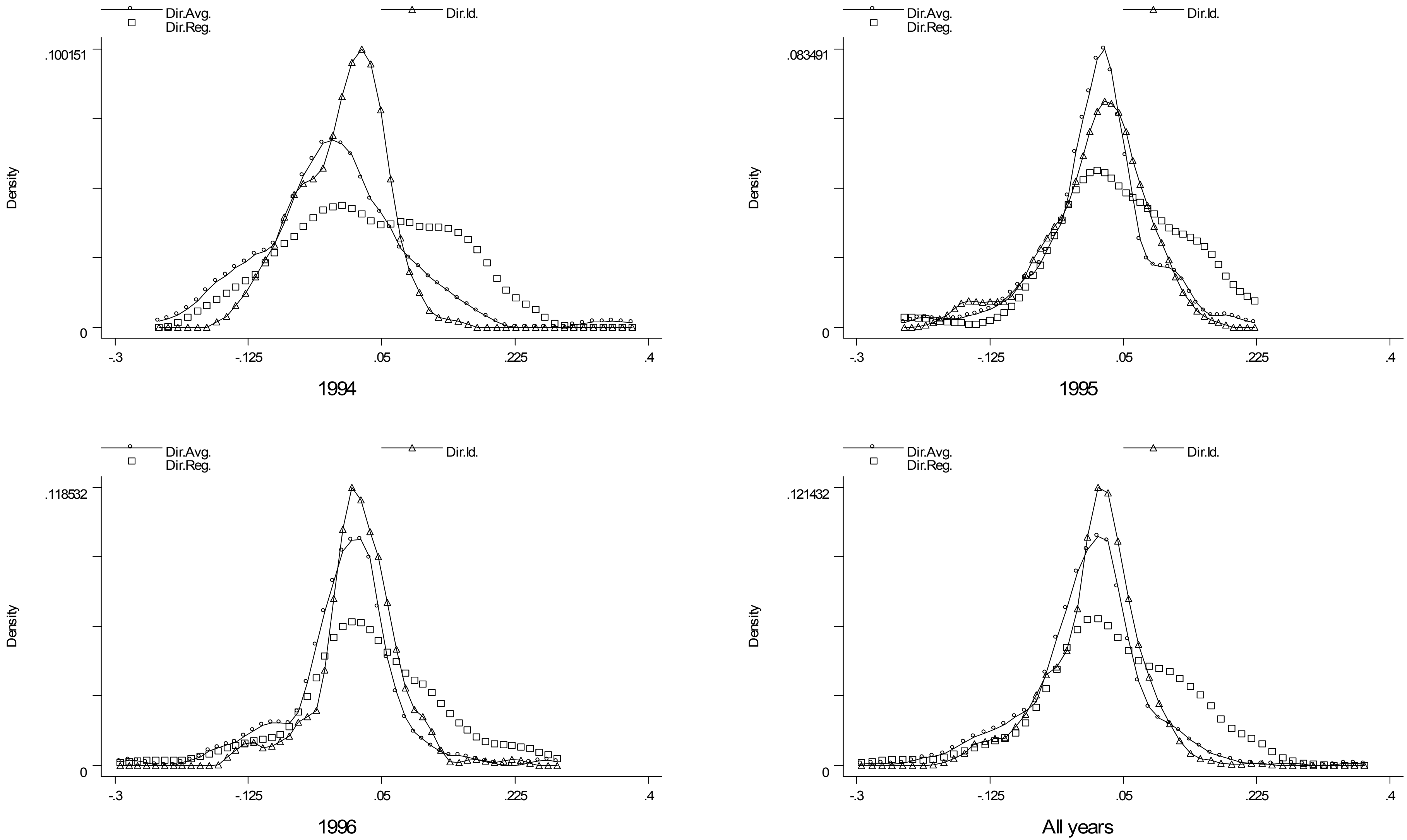
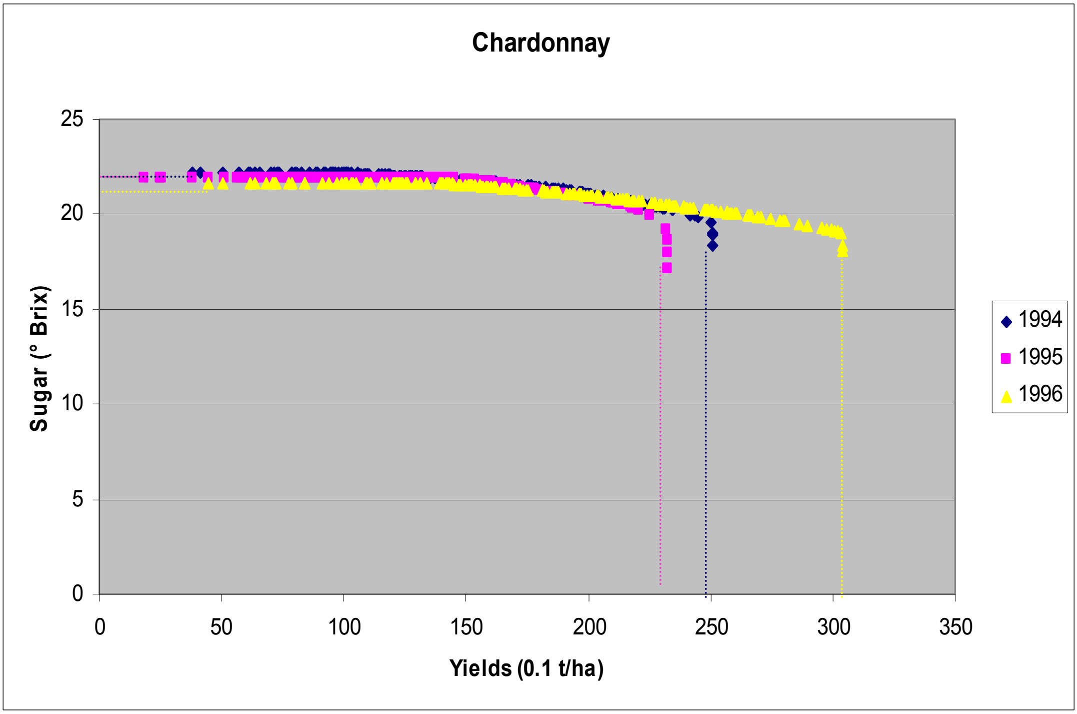


Figure 12B Luenberg Quality Indicators –WDO MERLOT



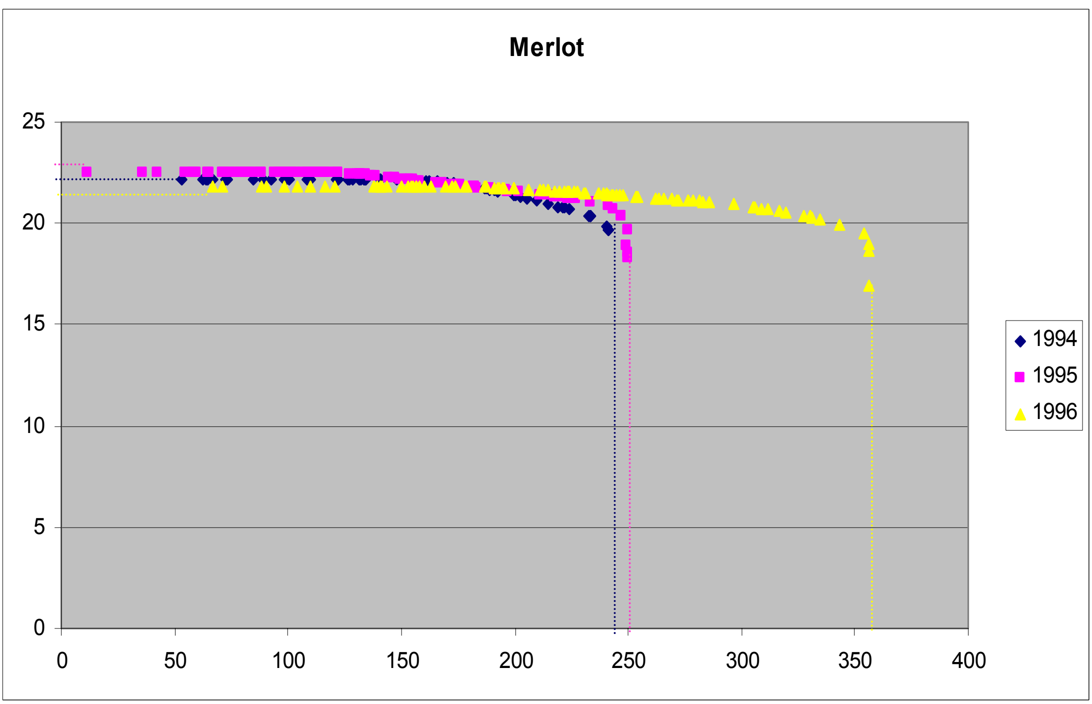


Figure 13. Output Isoquants: Yields/Sugar content

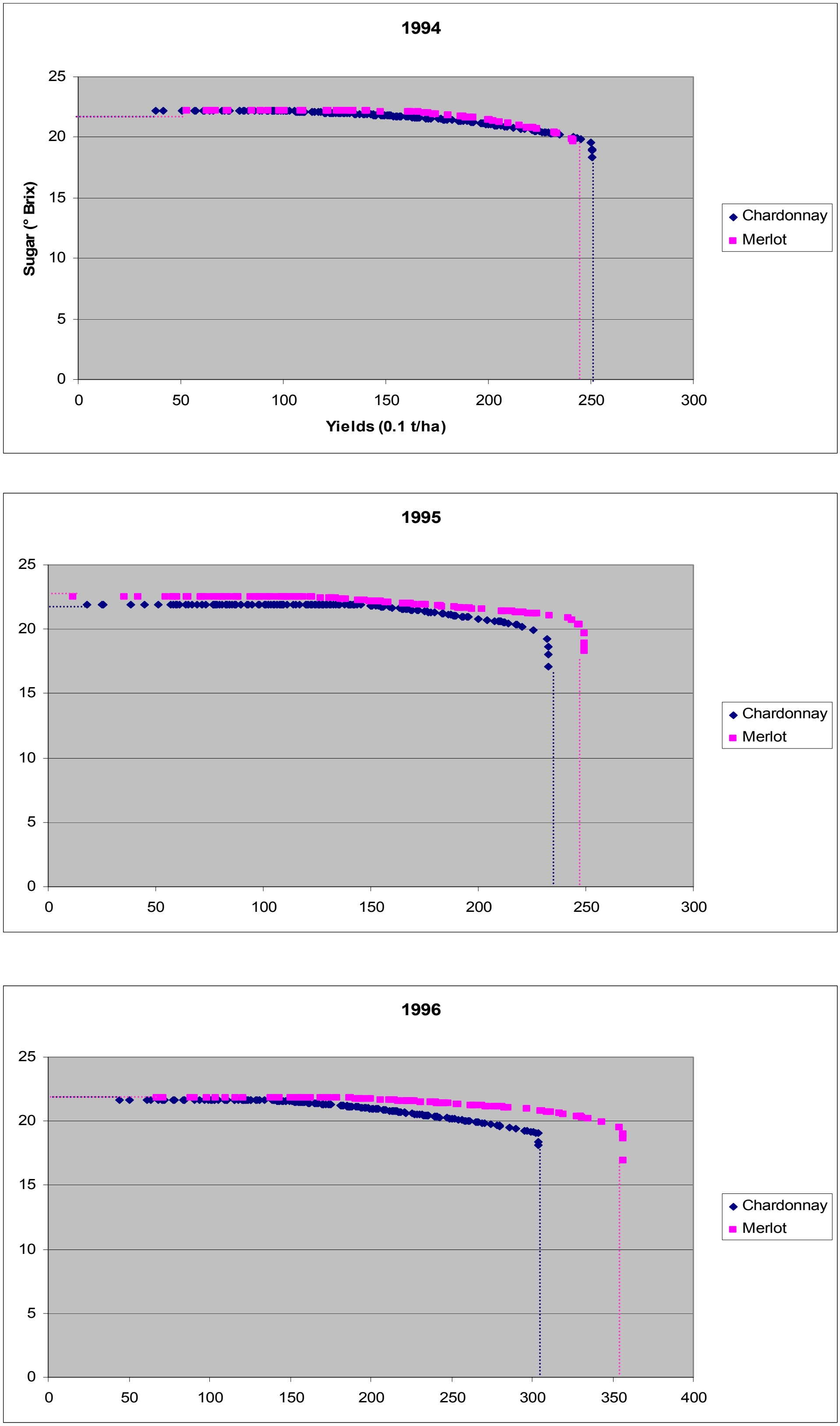


Figure 14. Output Isoquants: Yields/Sugar content

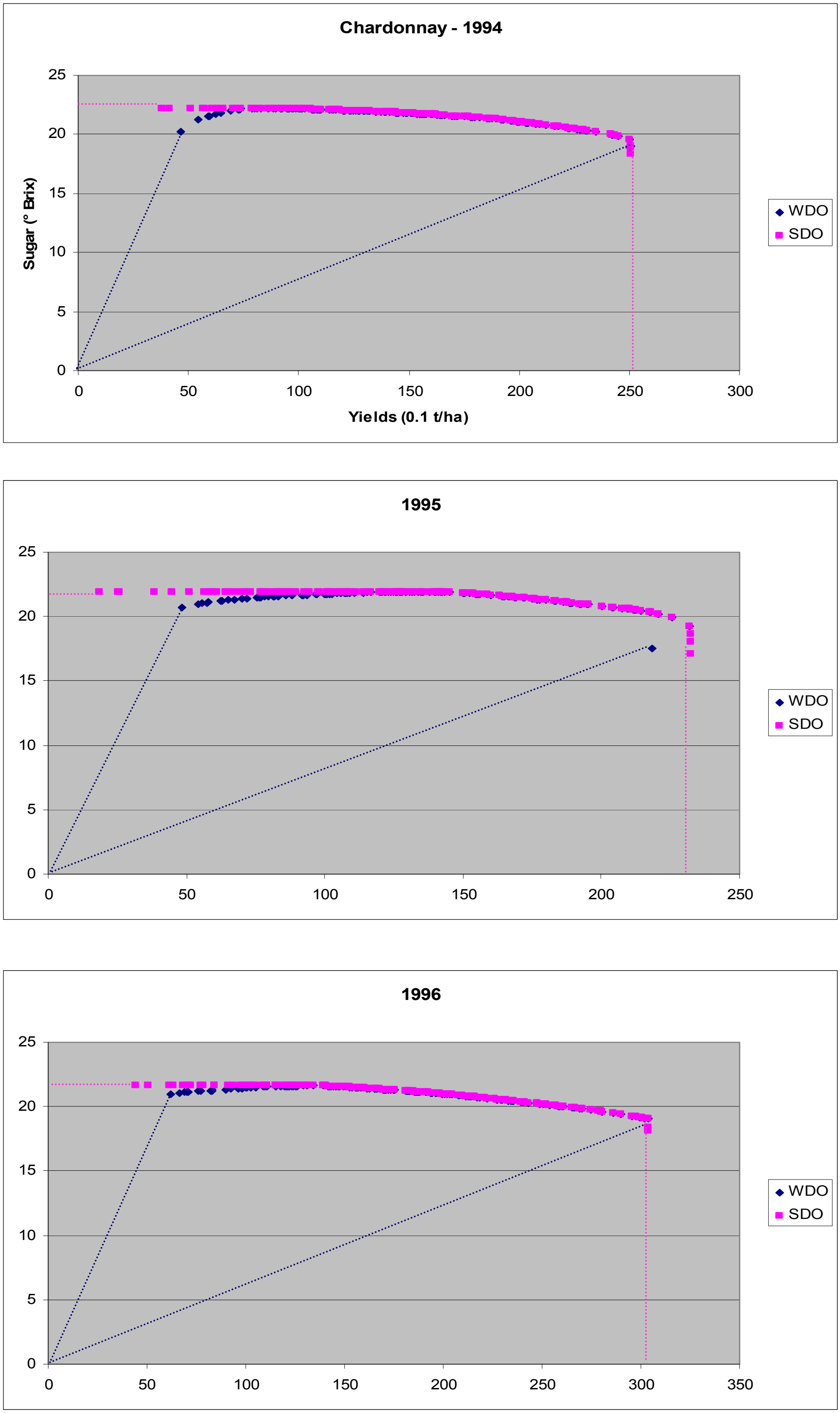
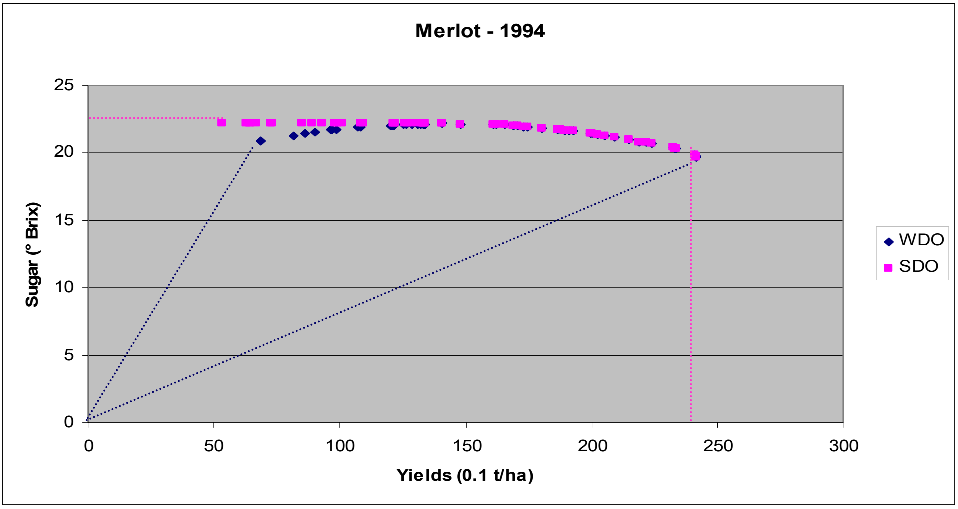
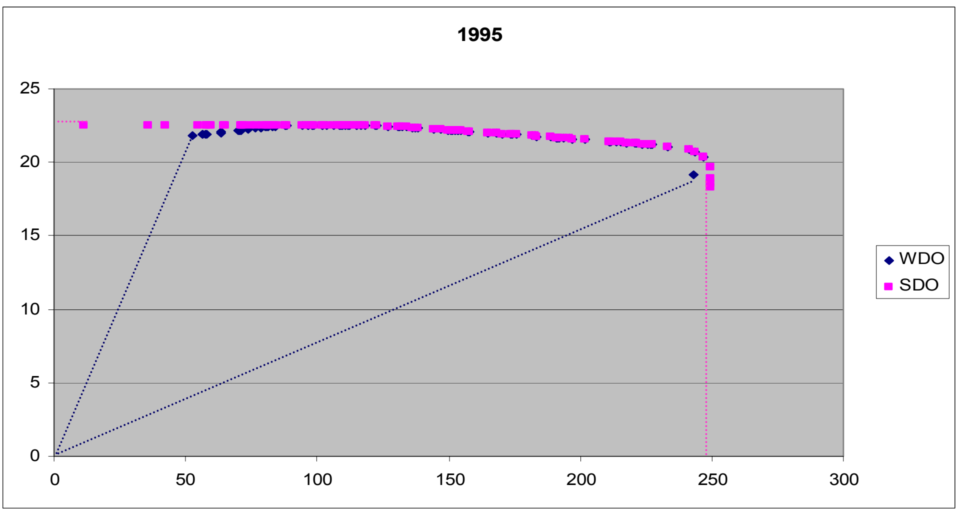


Figure 15. Output Isoquants: Yields/Sugar content





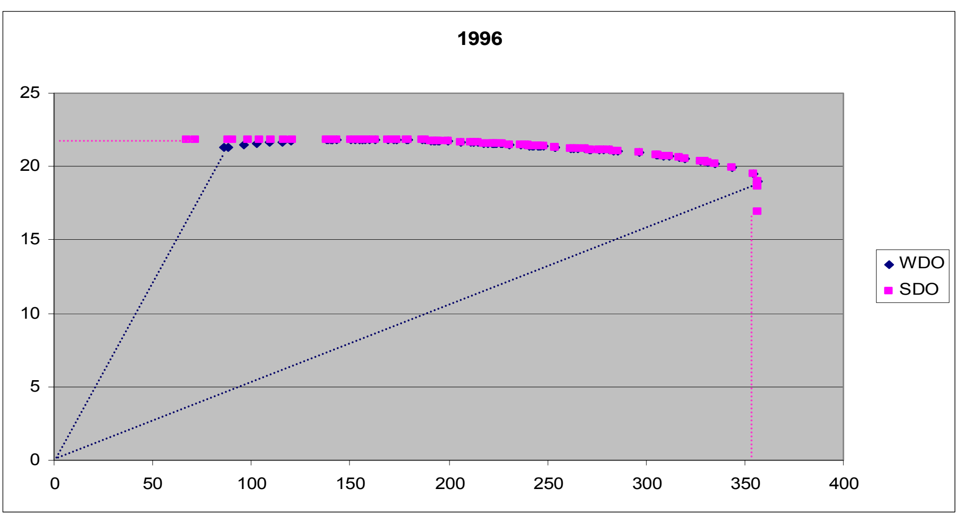
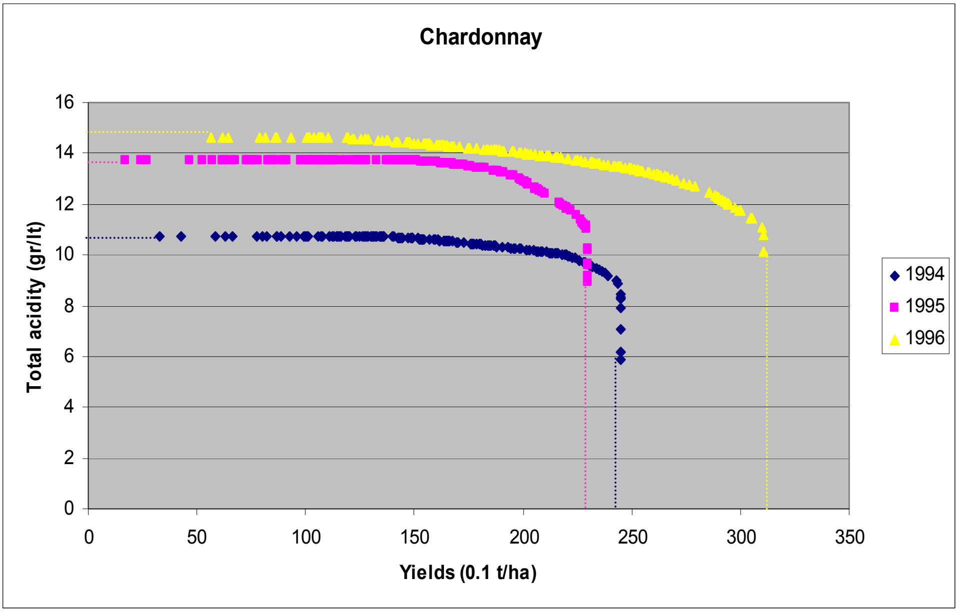


Figure 16. Output Isoquants: Yields/Sugar content



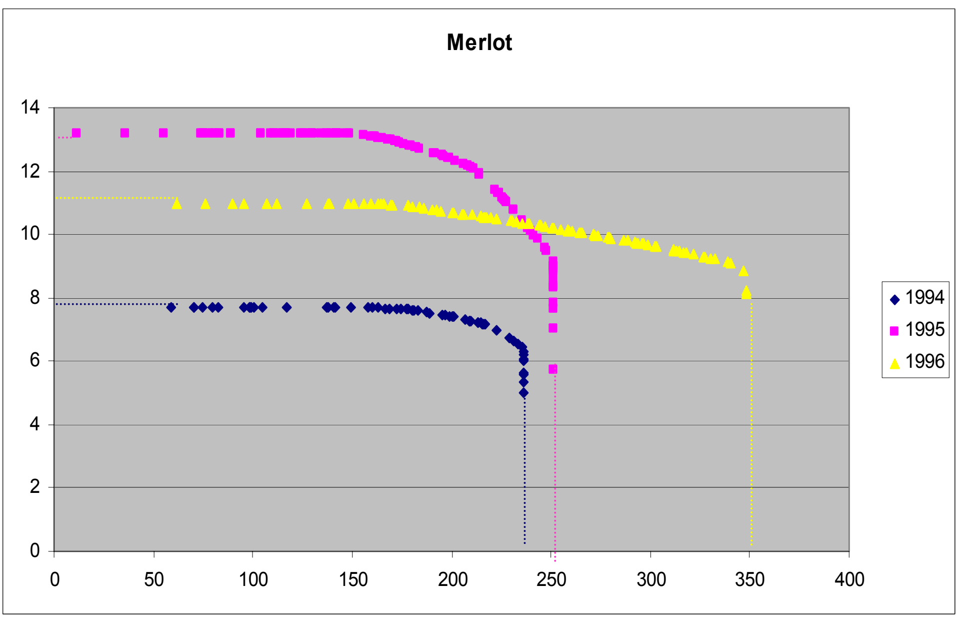


Figure 17. Output Isoquants: Yields/Total acidity

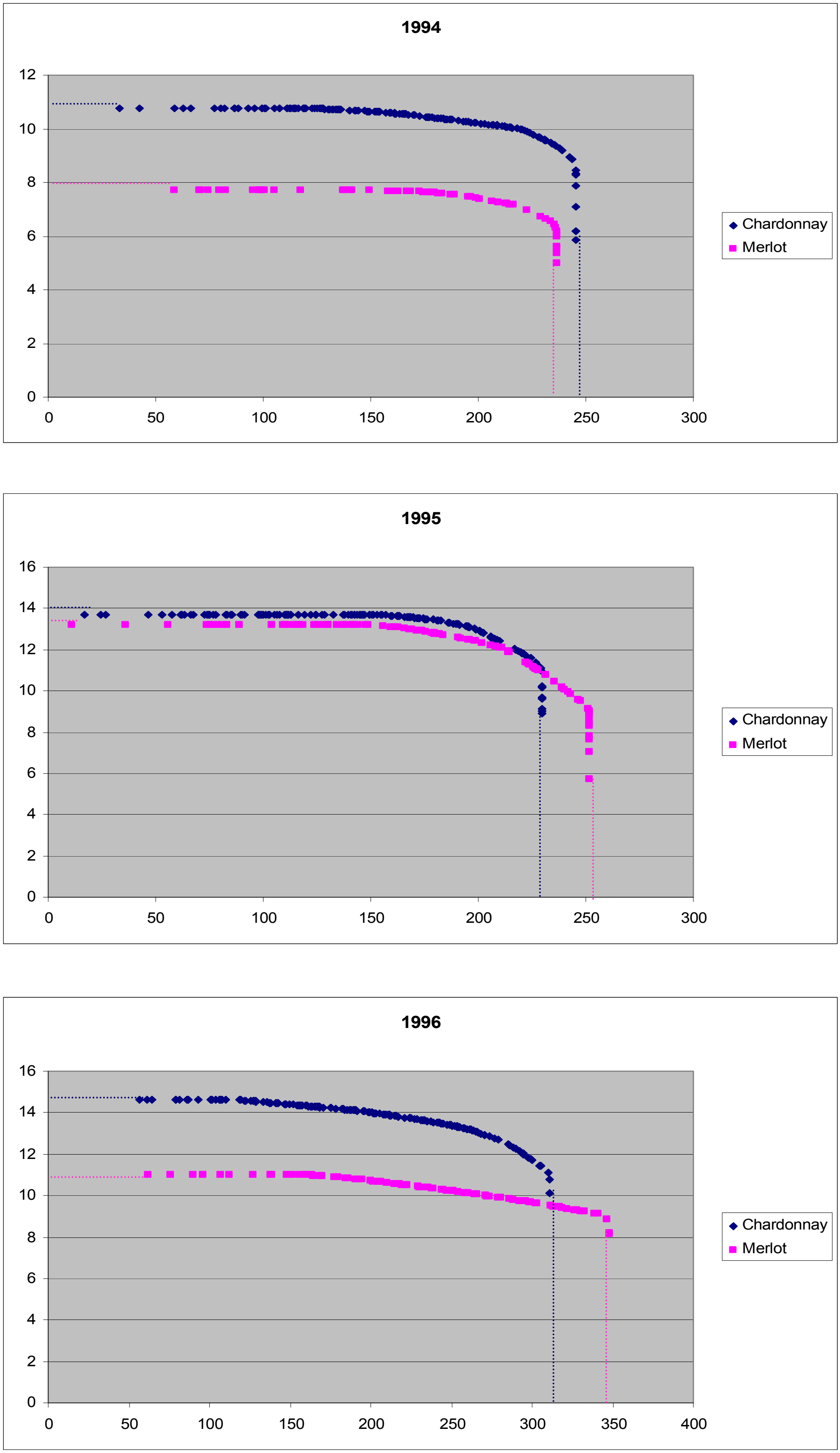


Figure 18. Output Isoquants: Yields/Total acidity

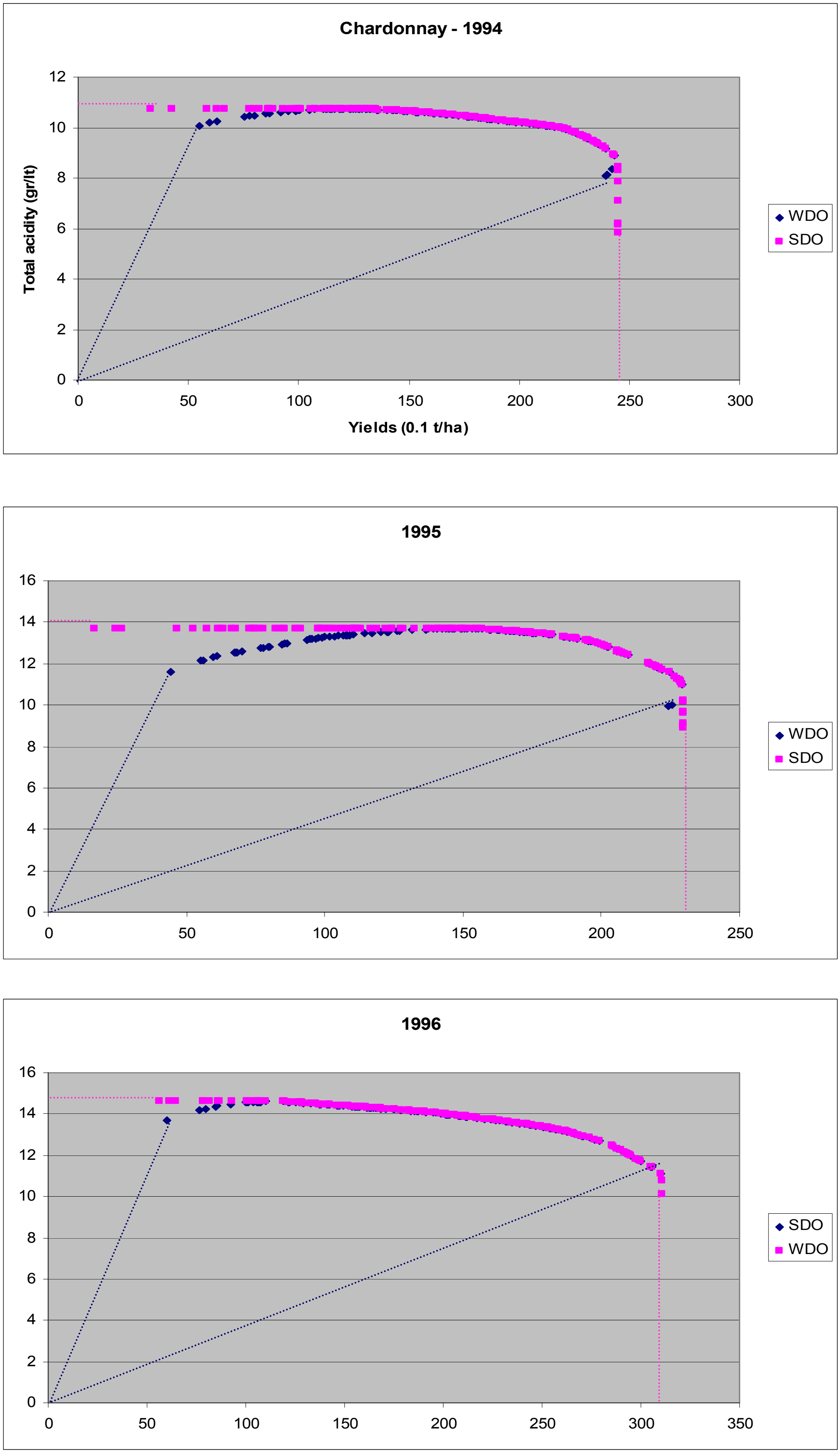


Figure 19. Output Isoquants: Yields/Total acidity

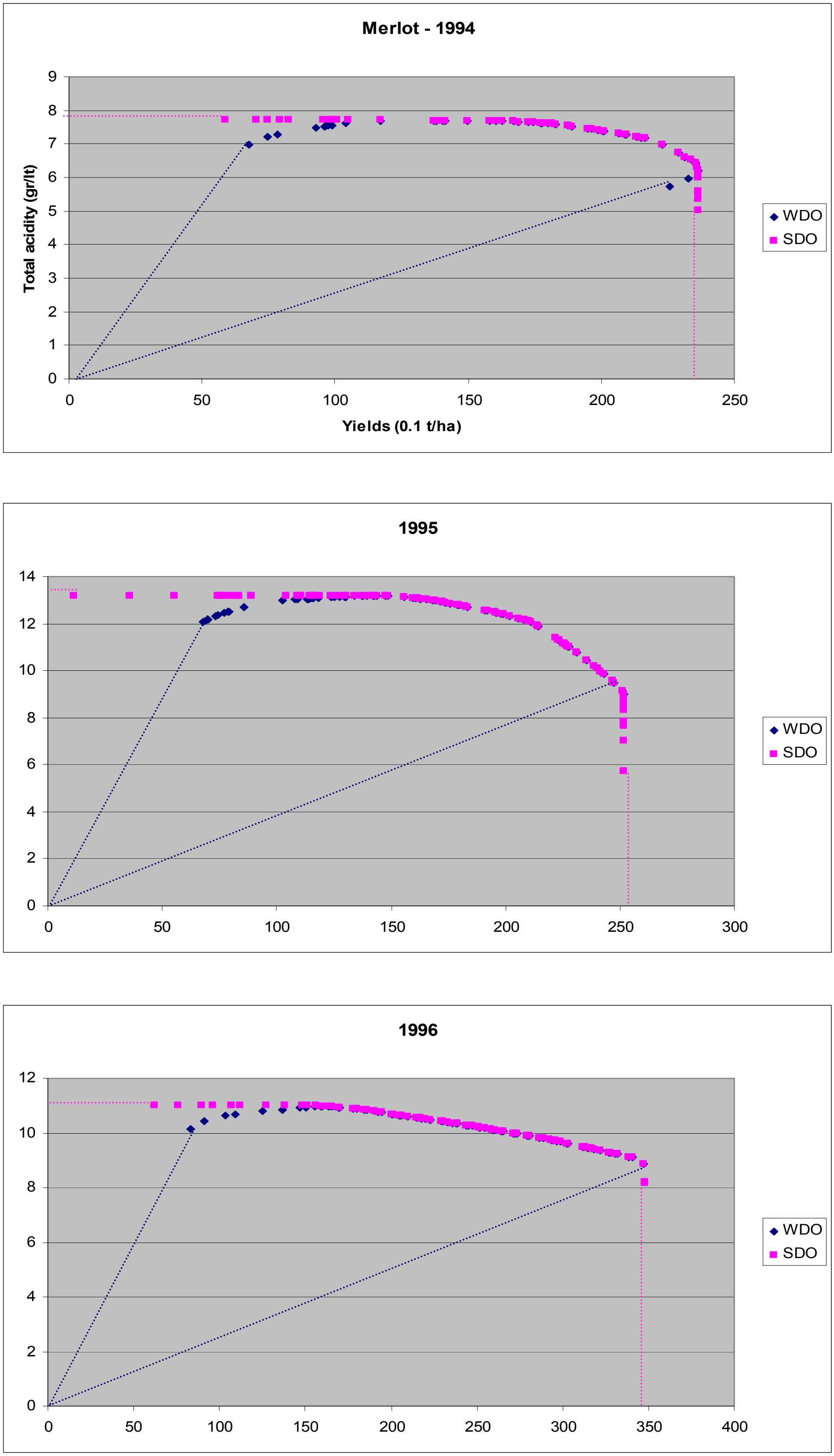
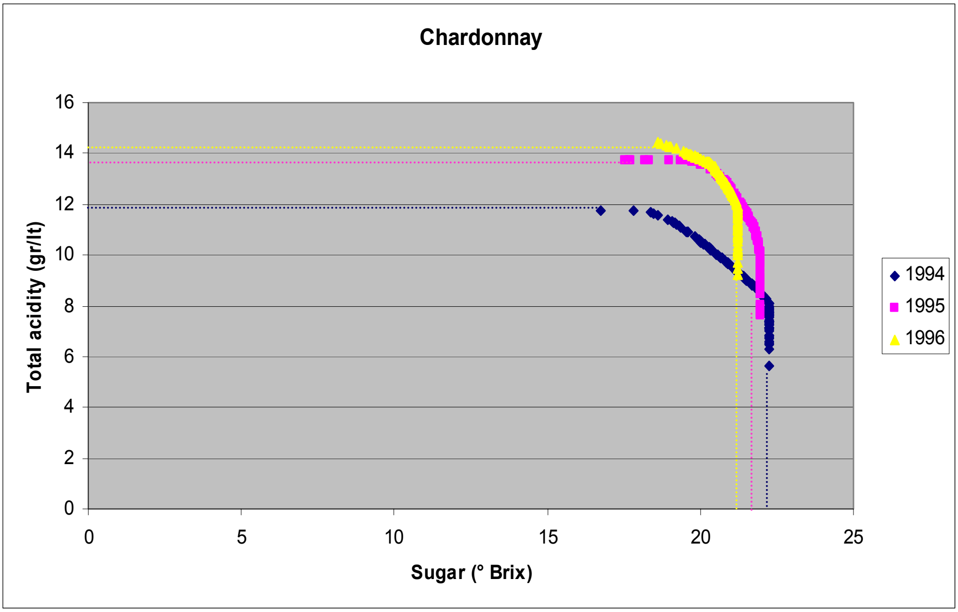


Figure 20. Output Isoquants: Yields/Total acidity



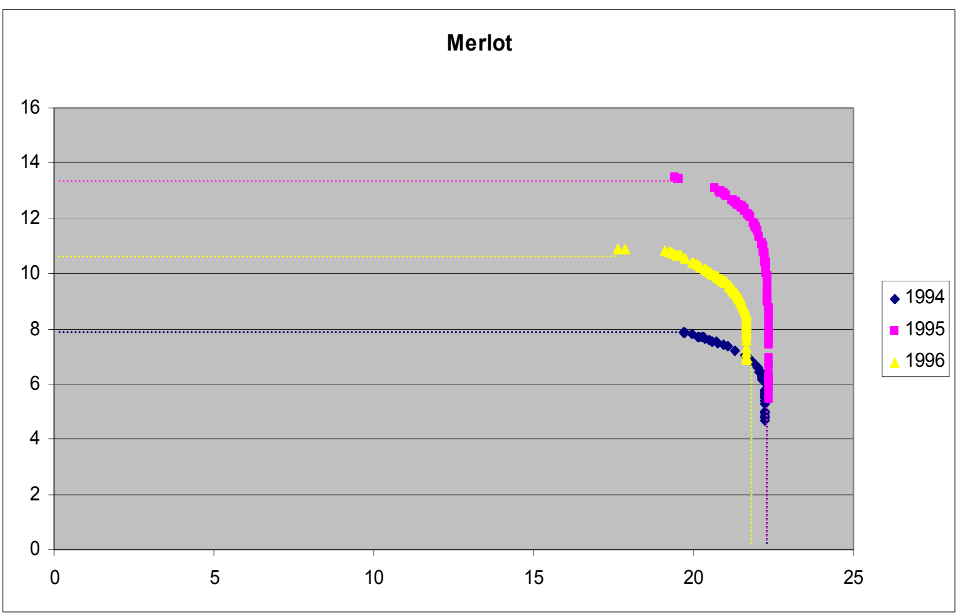


Figure 21. Output Isoquants: Sugar/Total acidity

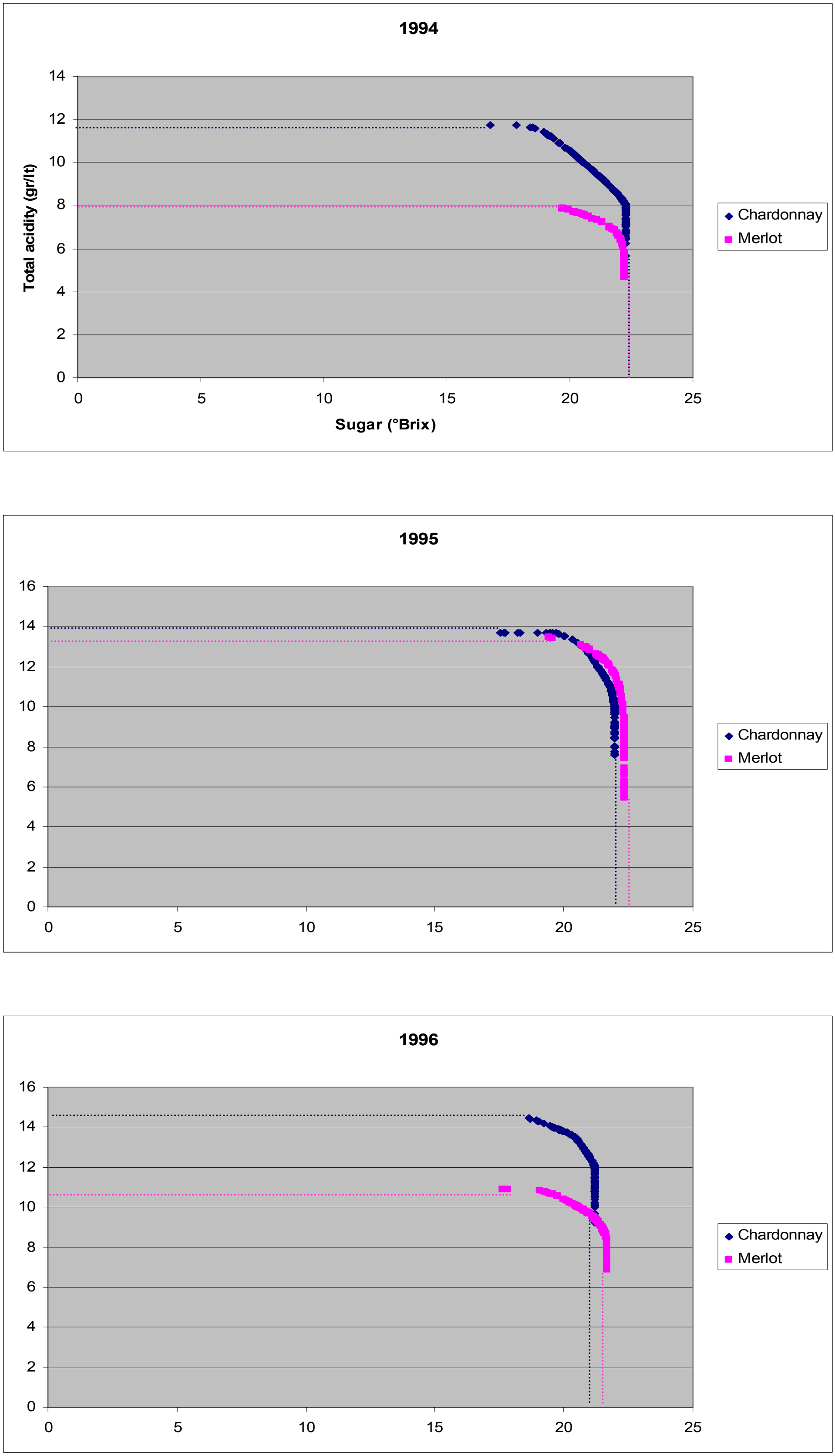


Figure 22. Output Isoquants: Sugar/Total acidity

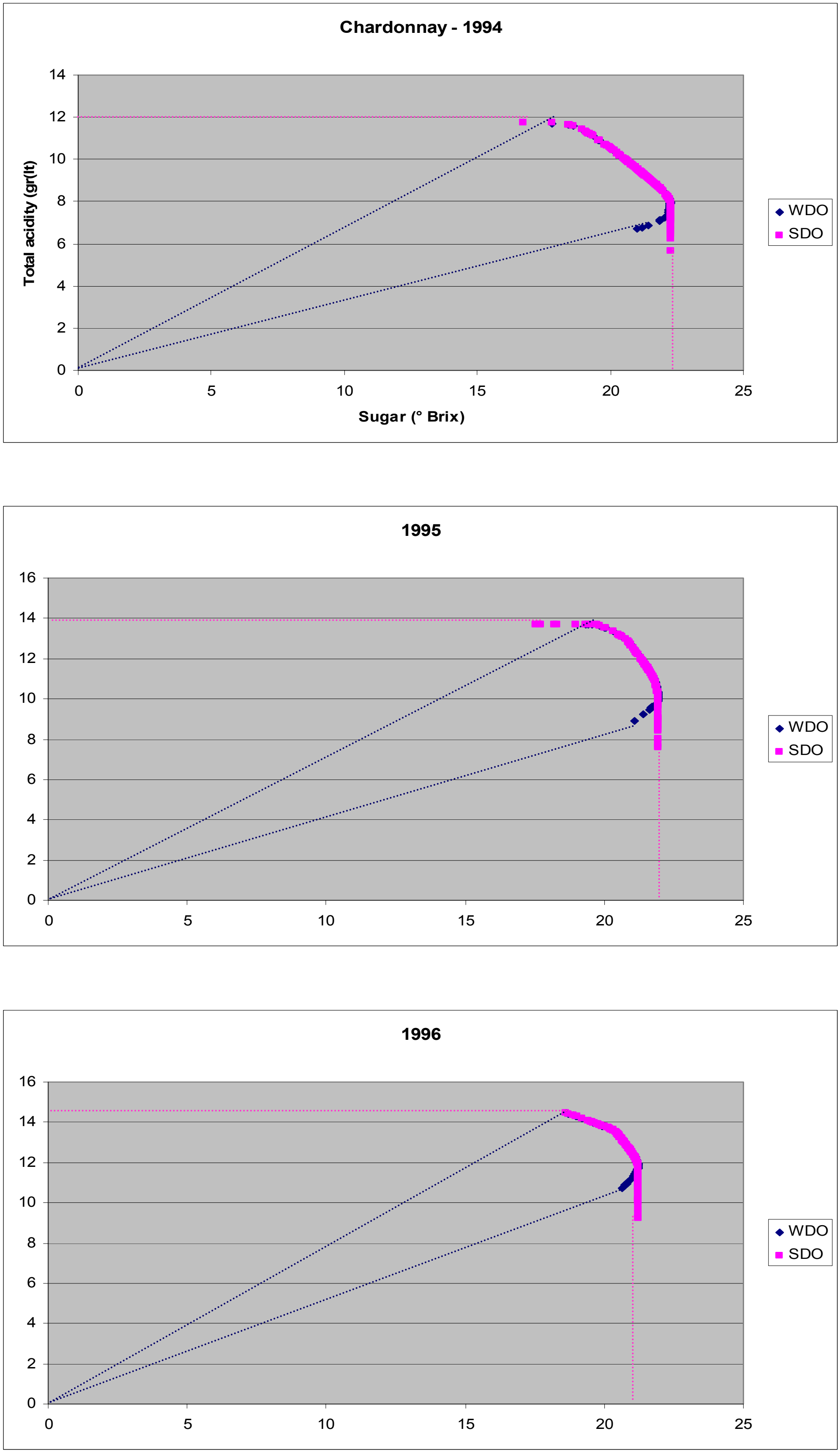


Figure 23. Output Isoquants: Sugar/Total acidity

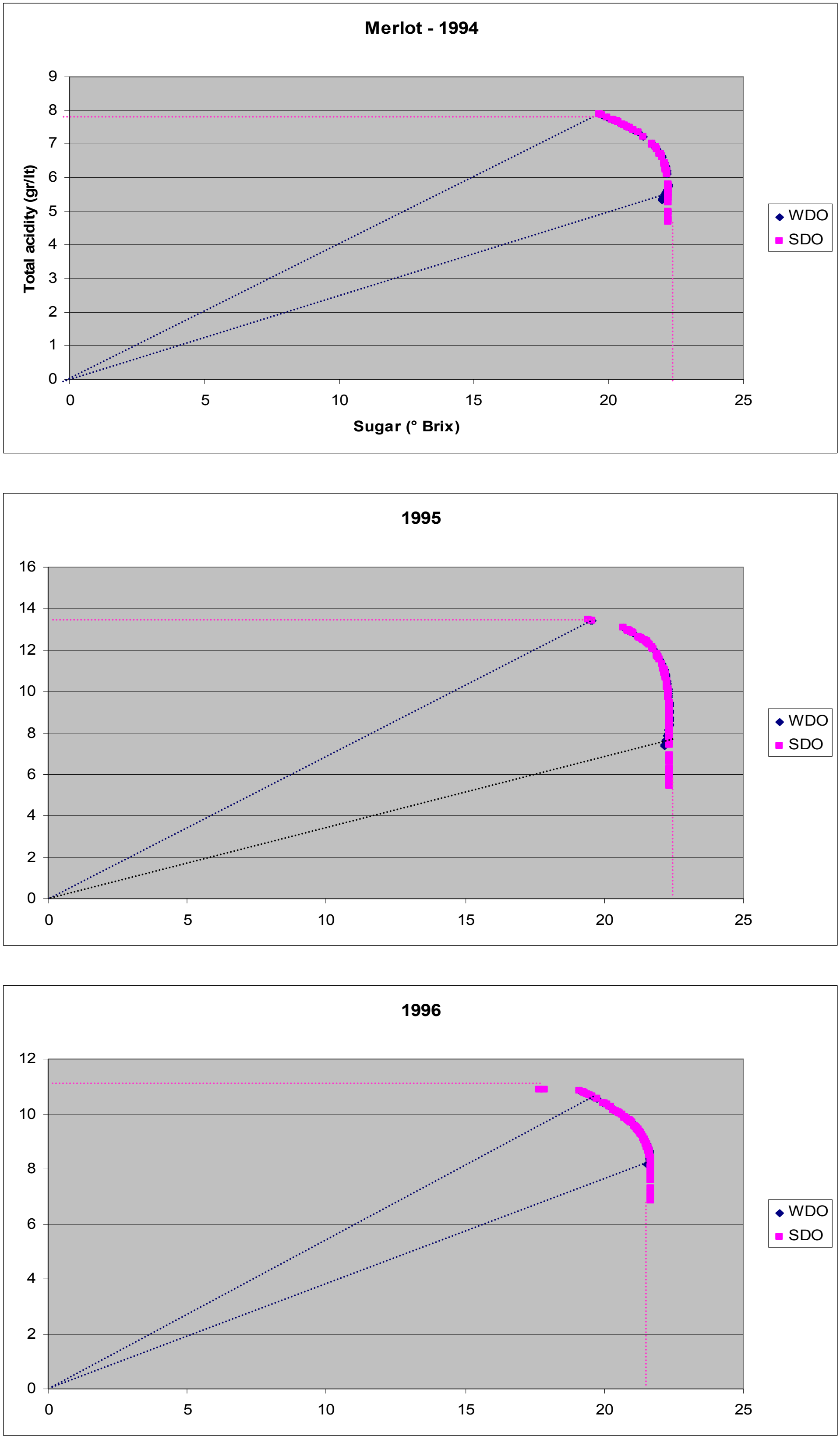
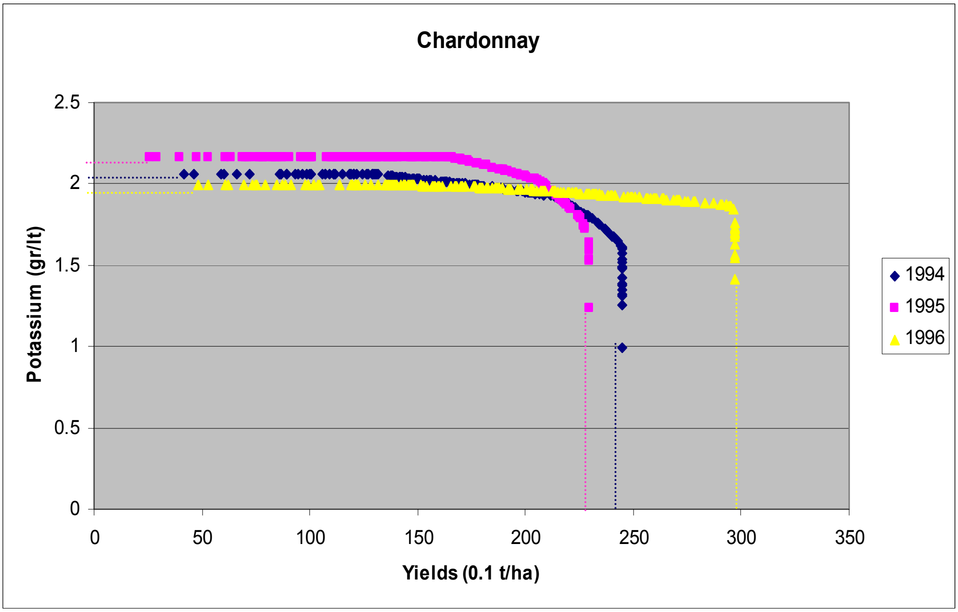


Figure 24. Output Isoquants: Sugar/Total acidity



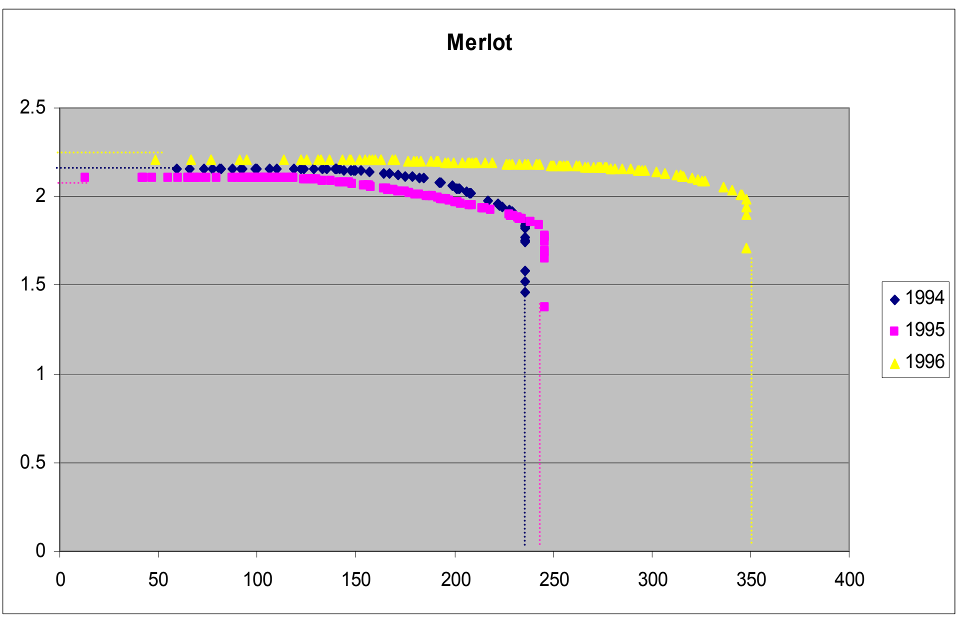
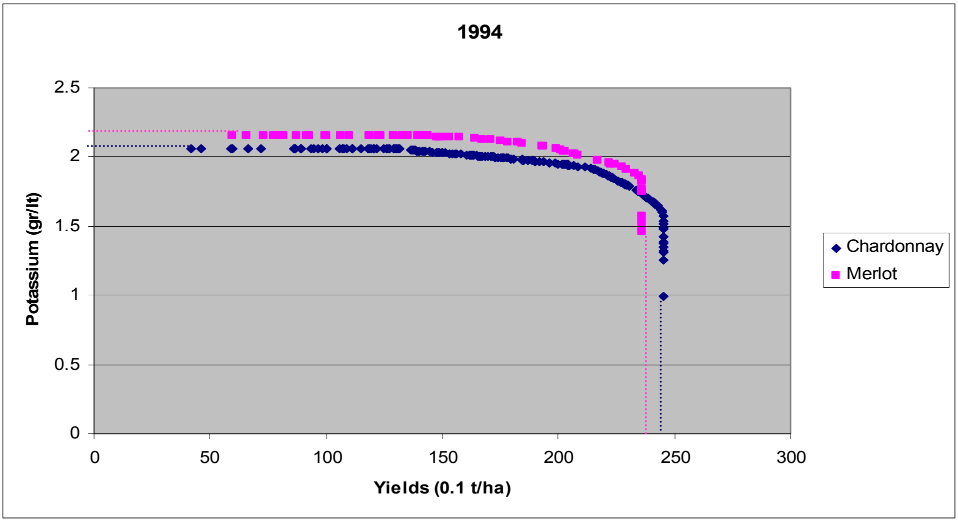
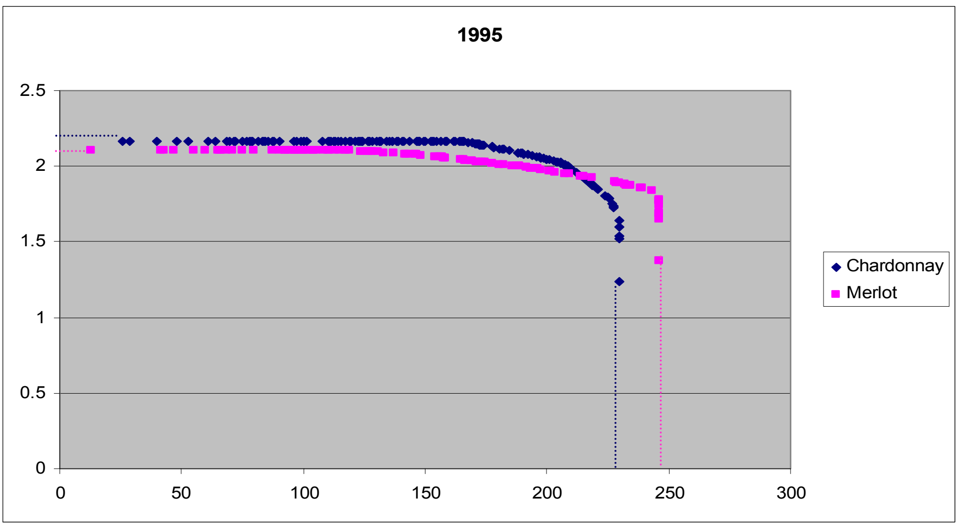


Figure 25. Output Isoquants: Yields/Potassium





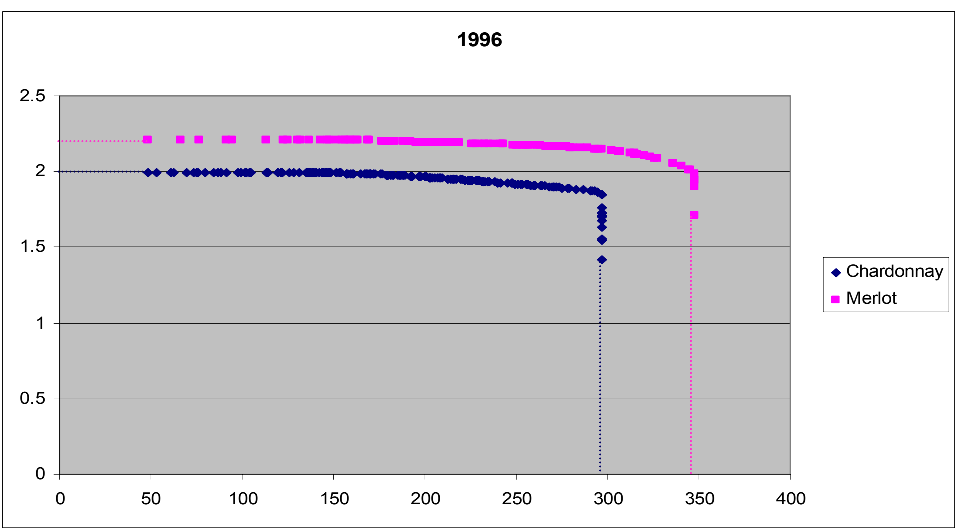
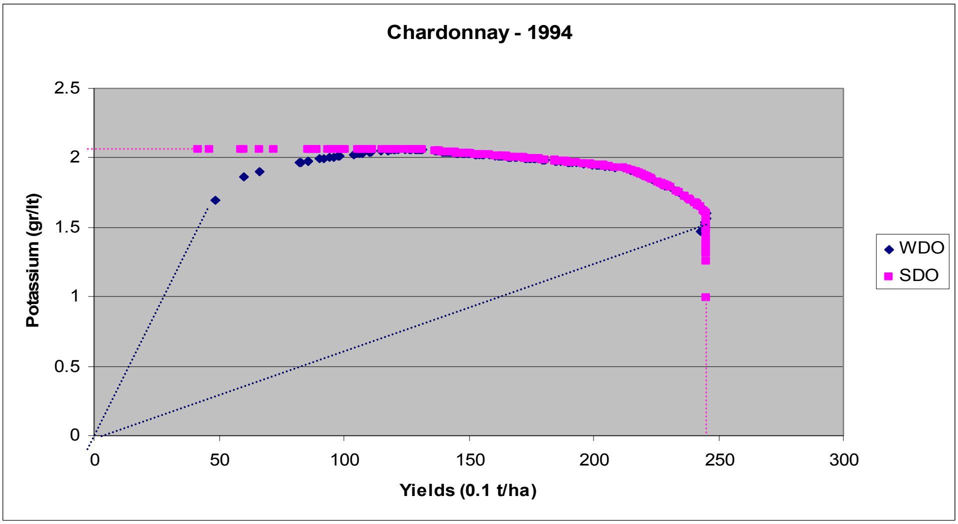
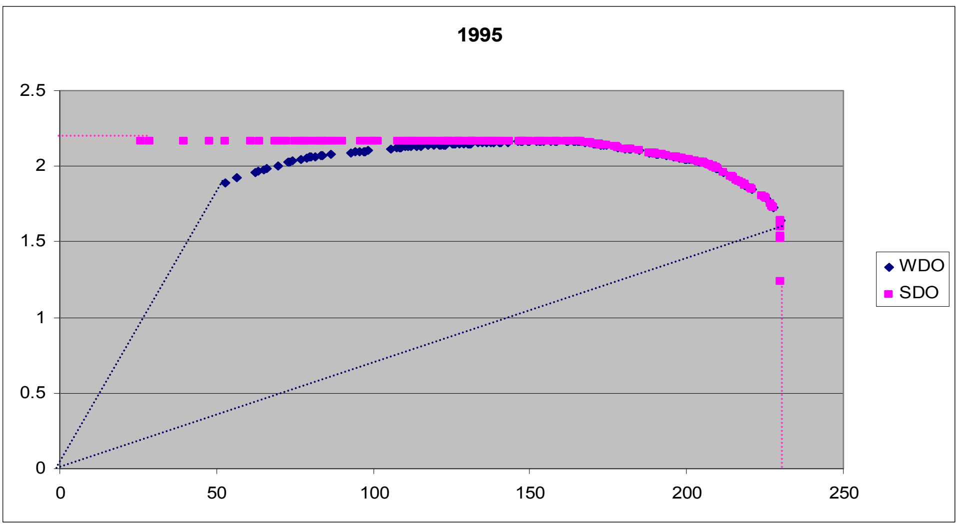


Figure 26. Output Isoquants: Yields/Potassium





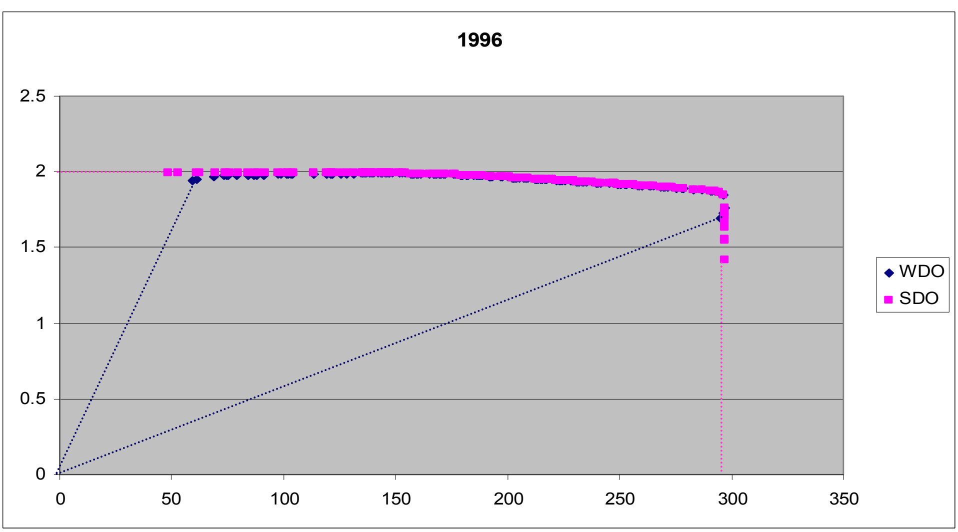


Figure 27. Output Isoquants: Yields/Potassium

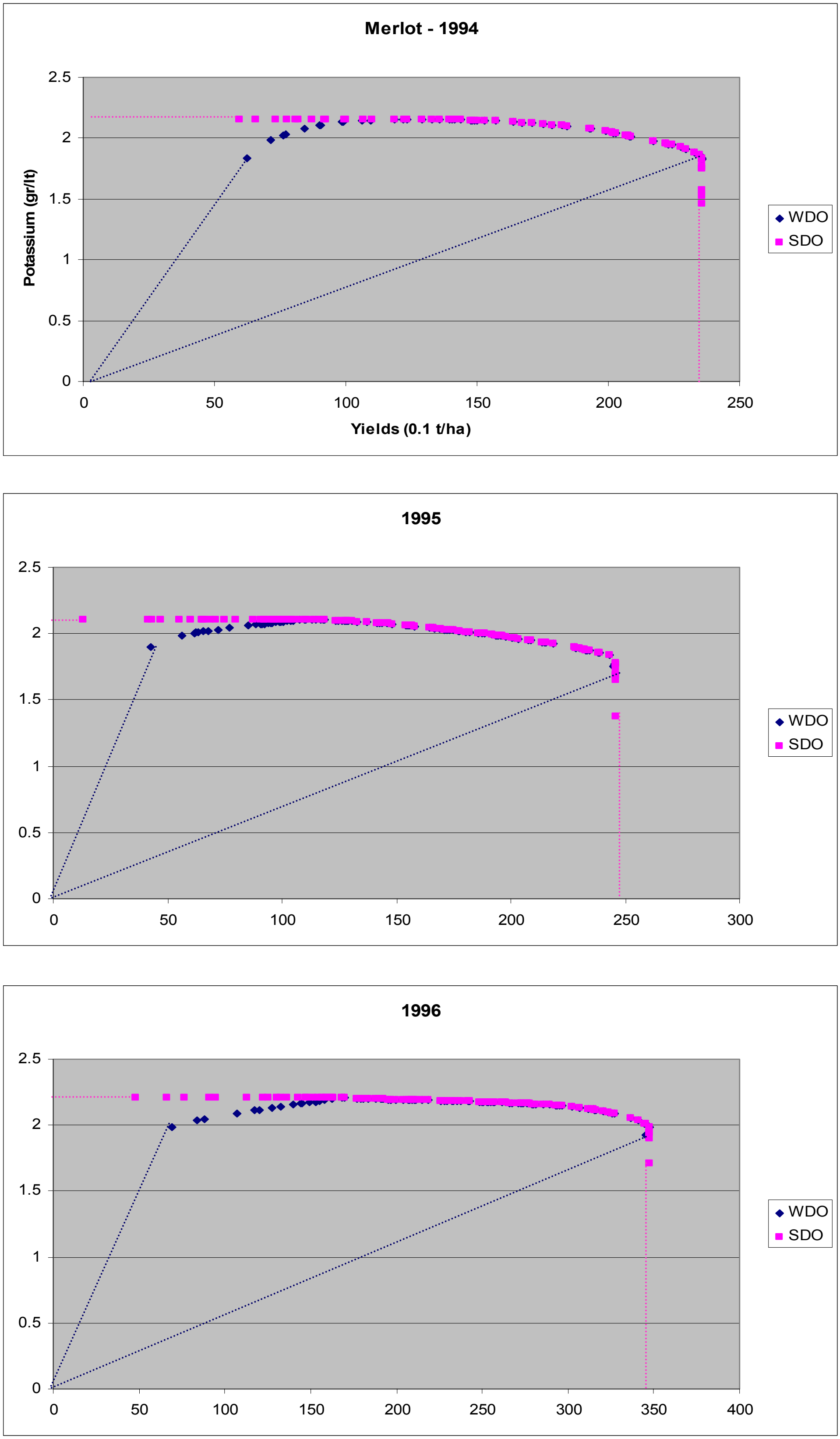


Figure 28. Output Isoquants: Yields/Potassium

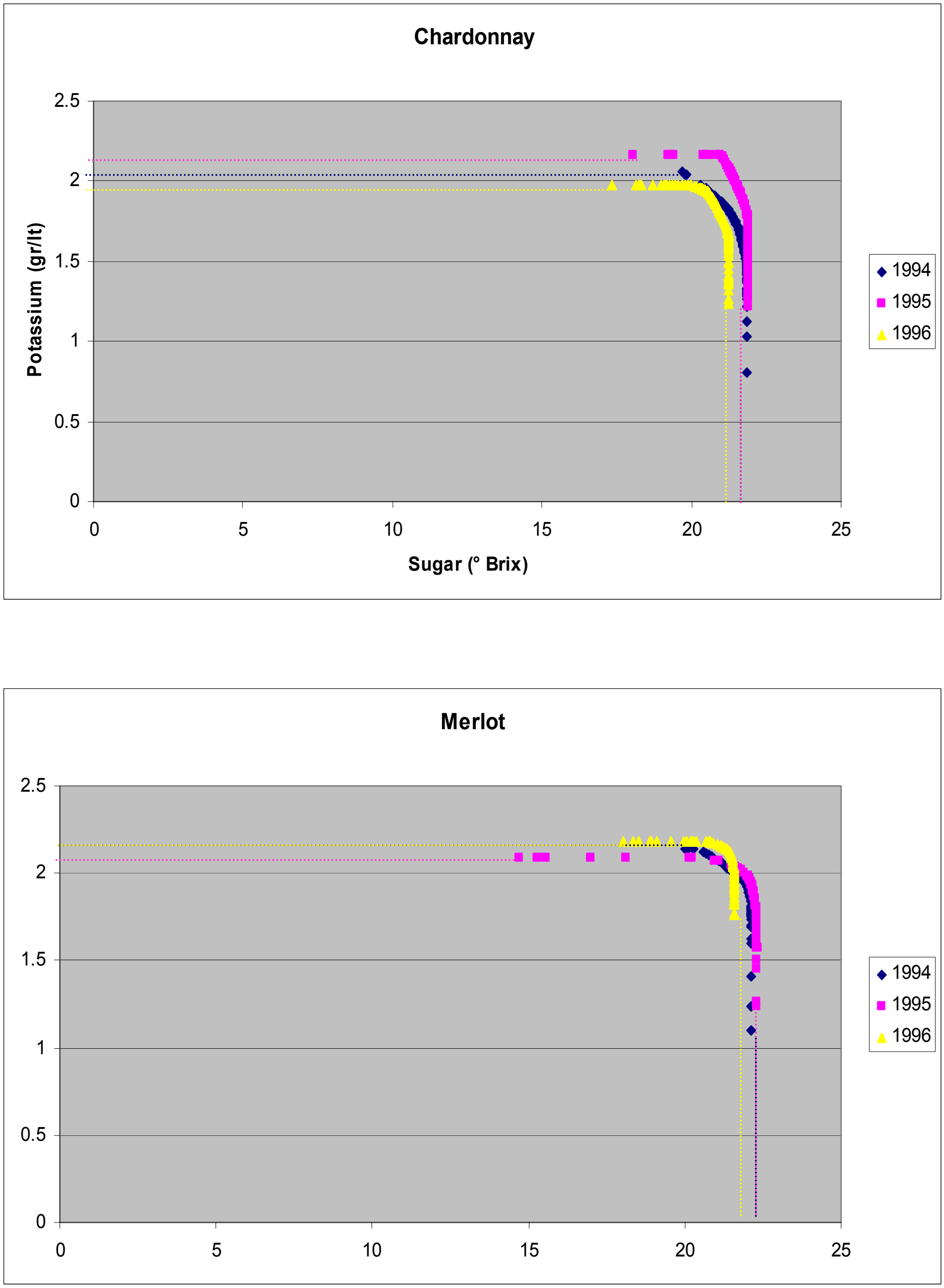


Figure 29. Output Isoquants: Sugar/Potassium

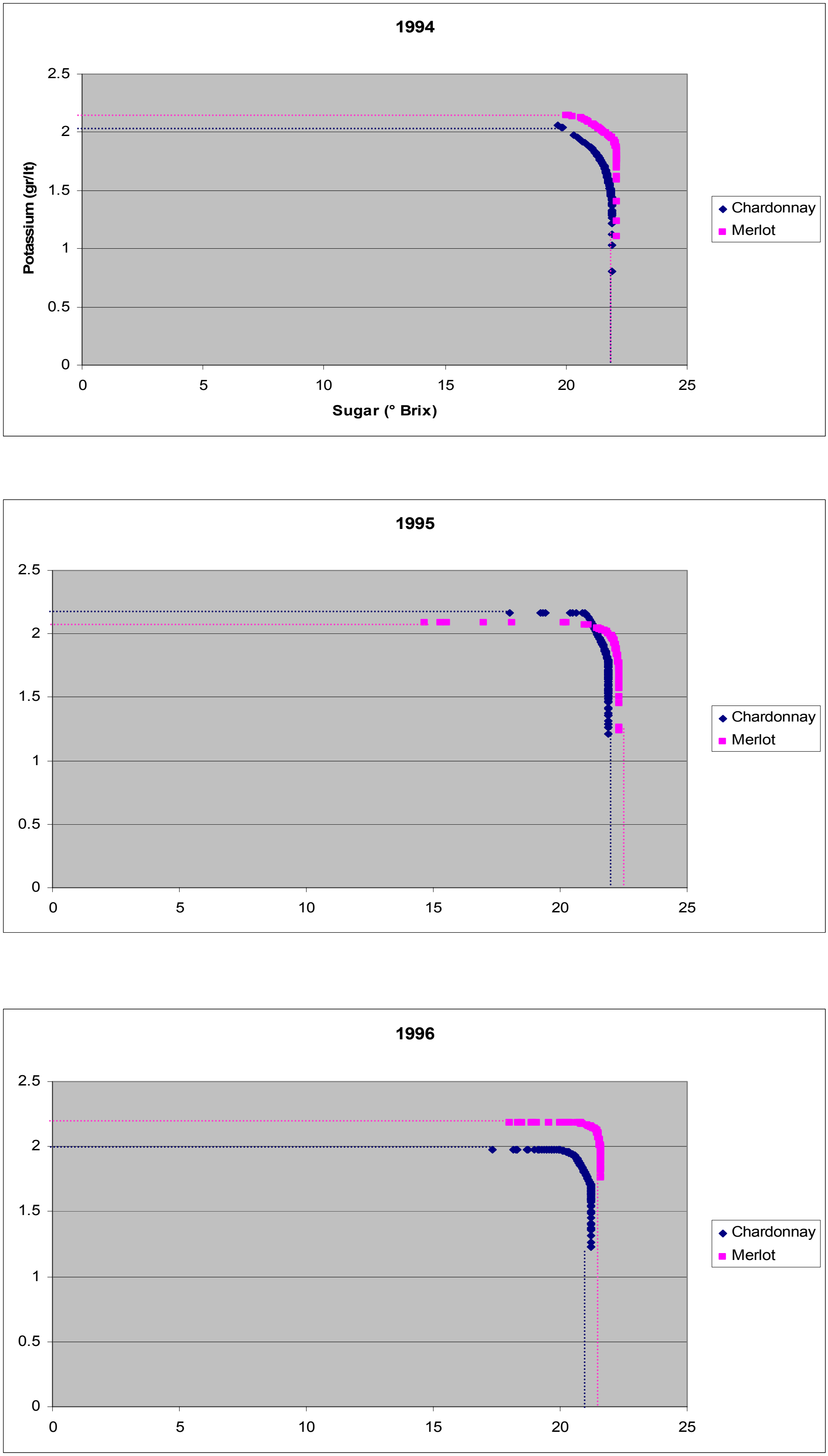


Figure 30. Output Isoquants: Sugar/Potassium

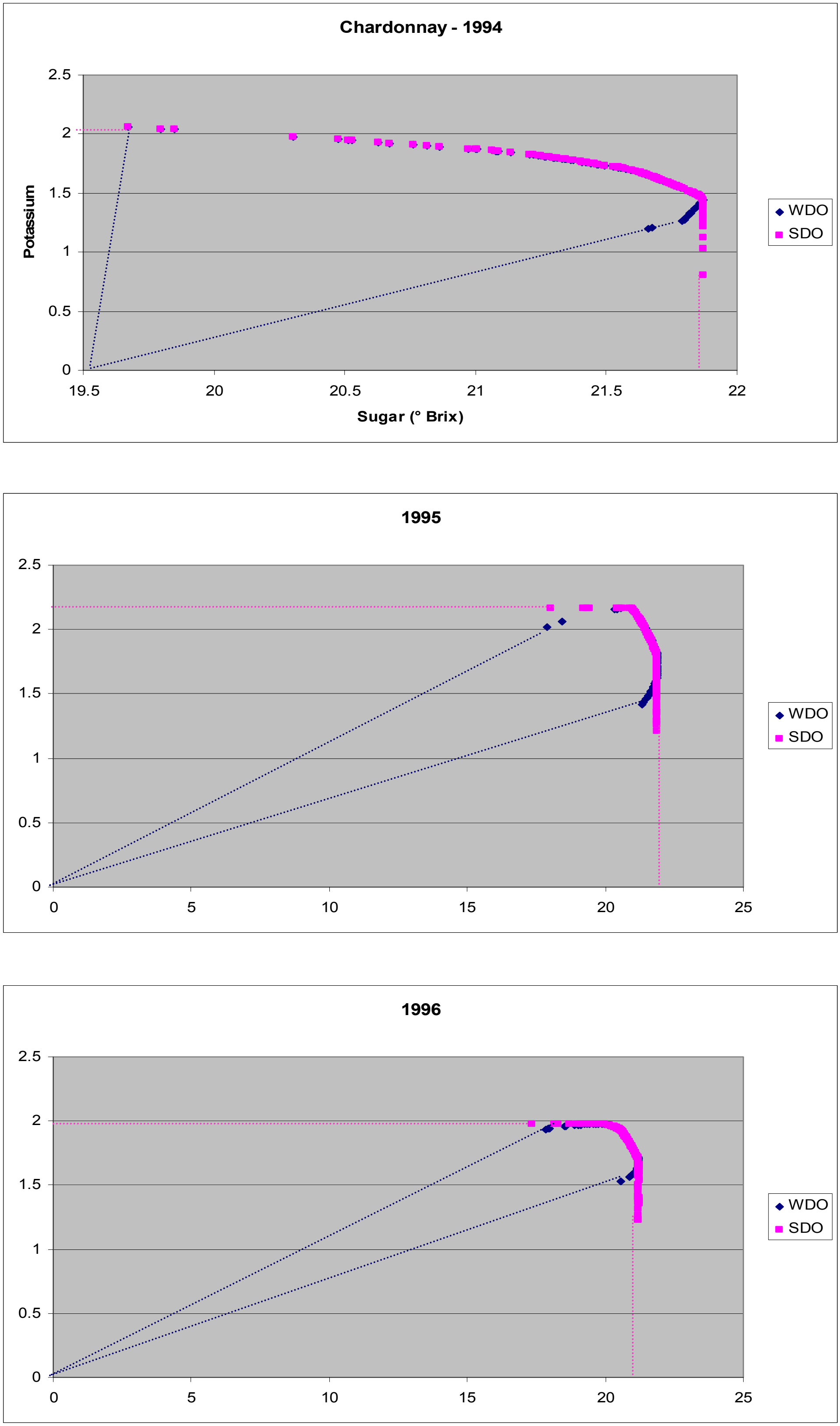


Figure 31. Output Isoquants: Sugar/Potassium

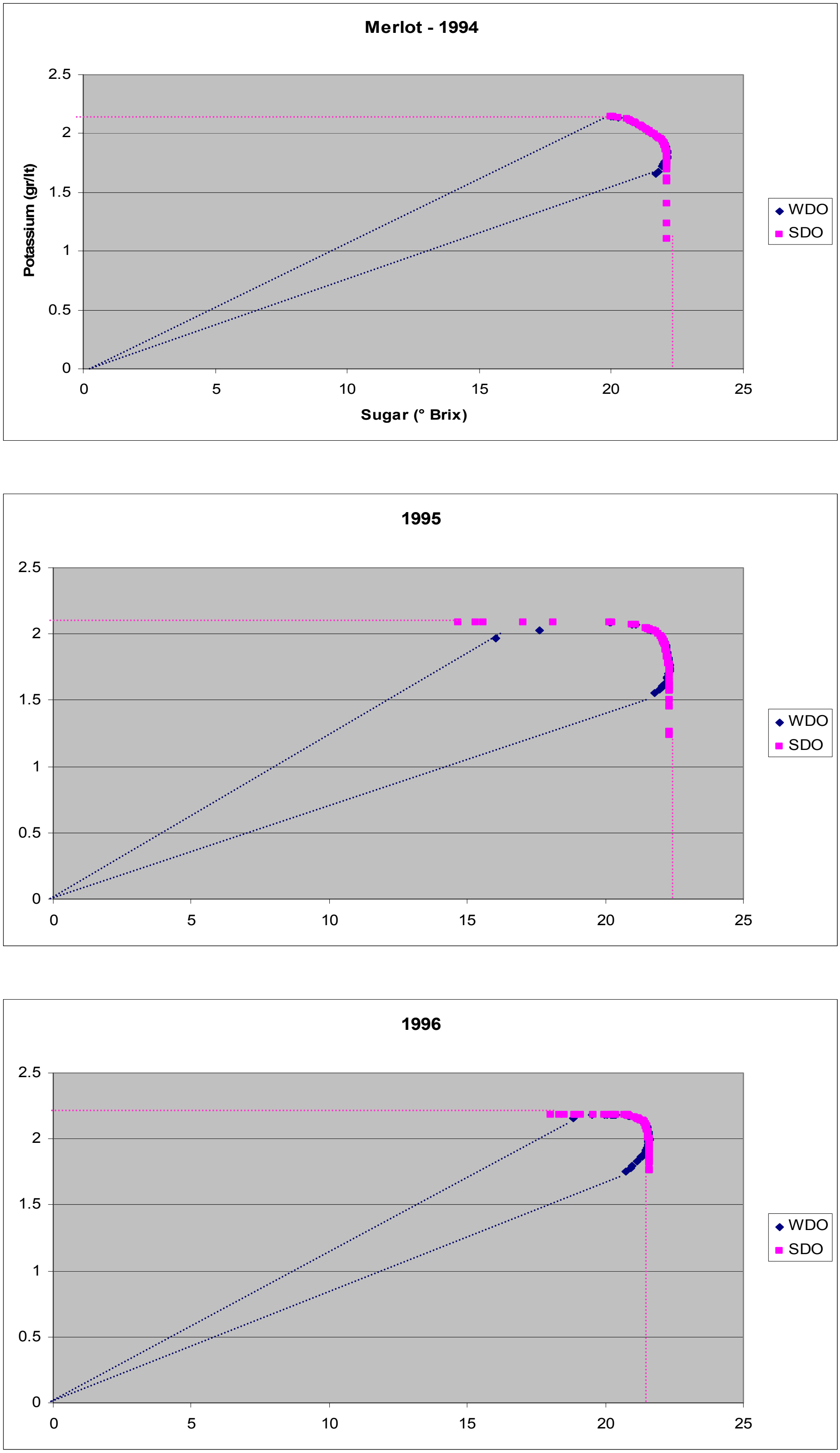


Figure 32. Output Isoquants: Sugar/Potassium

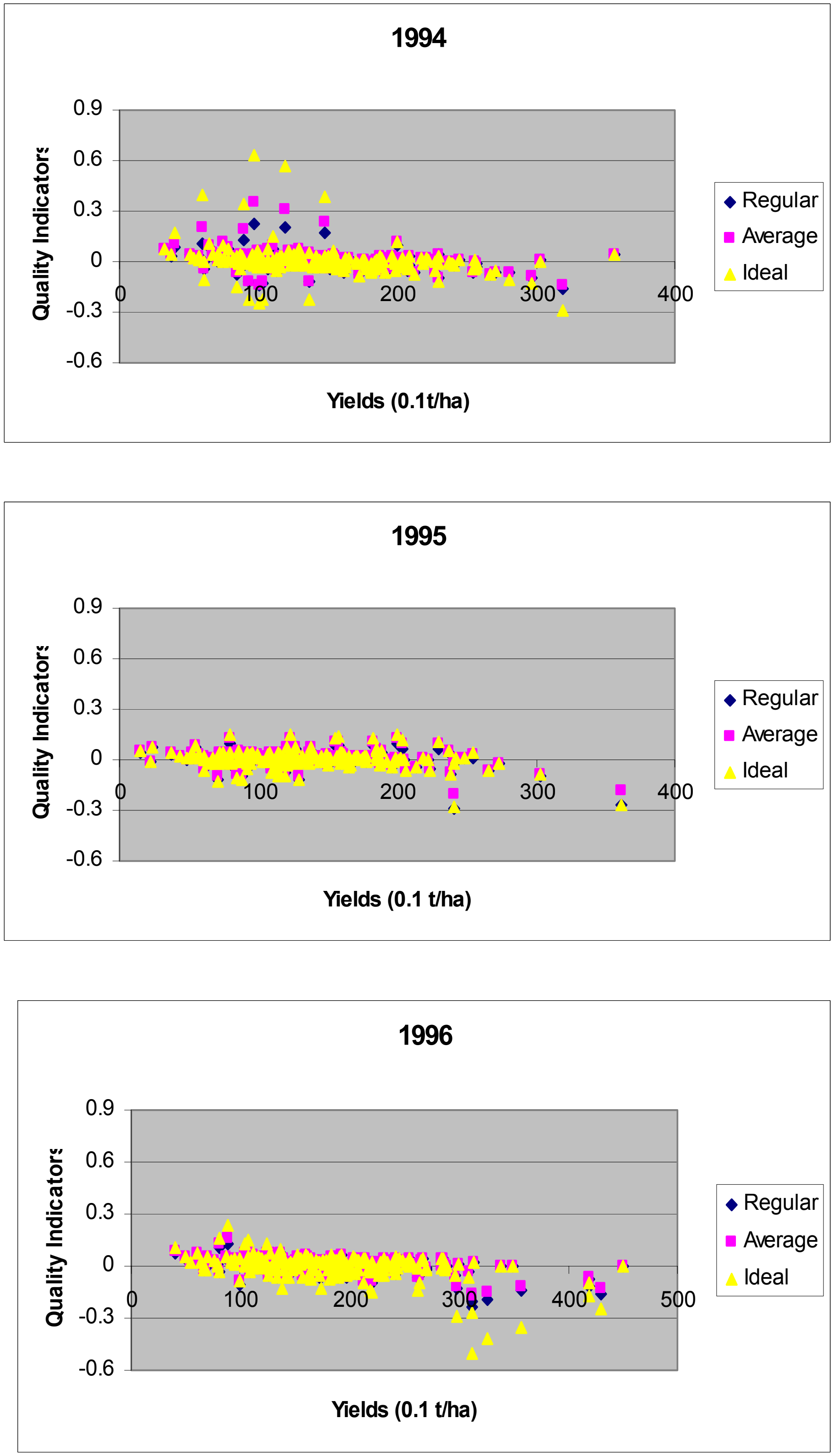


Figure 33. Quality Indicators vs. Yields: Chardonnay

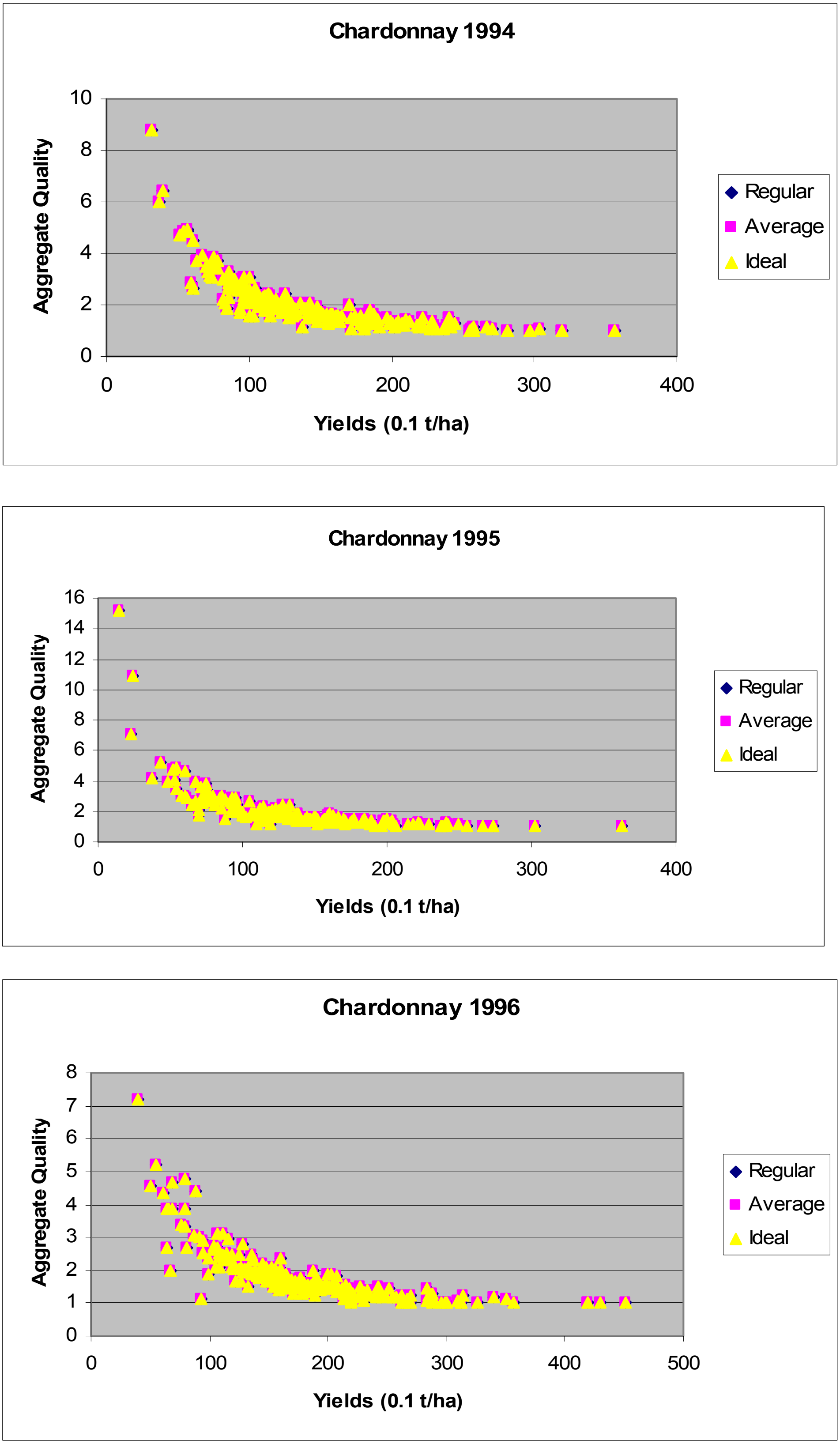
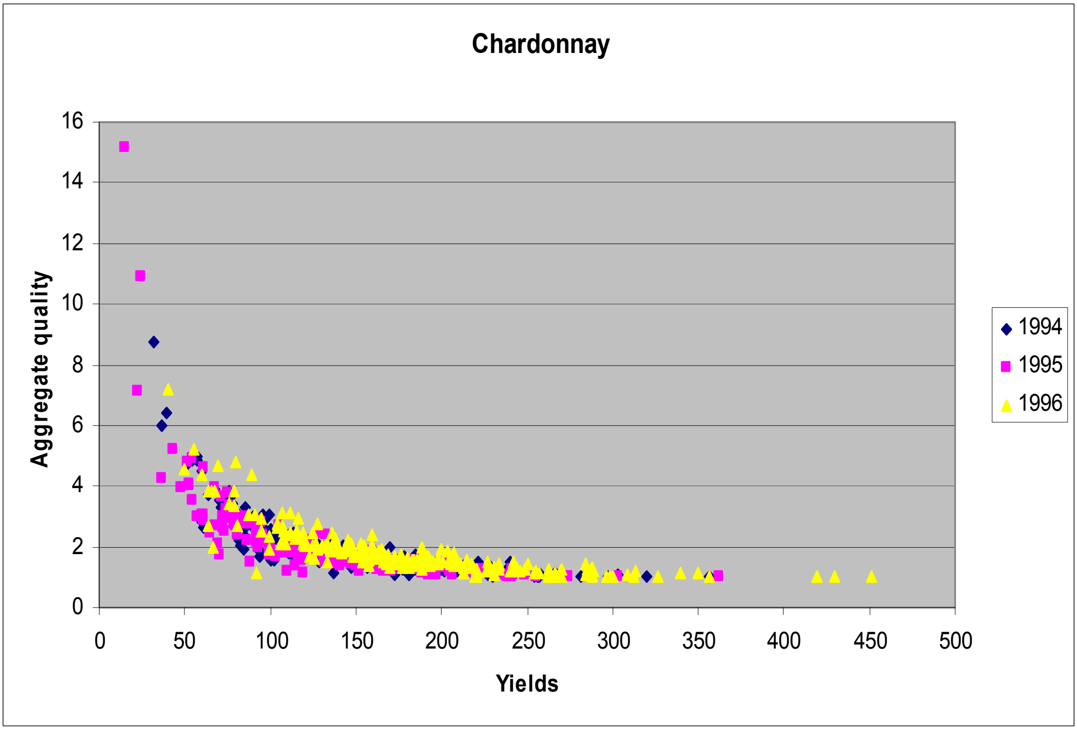


Figure 34. Aggregate Quality vs. Yields: Chardonnay



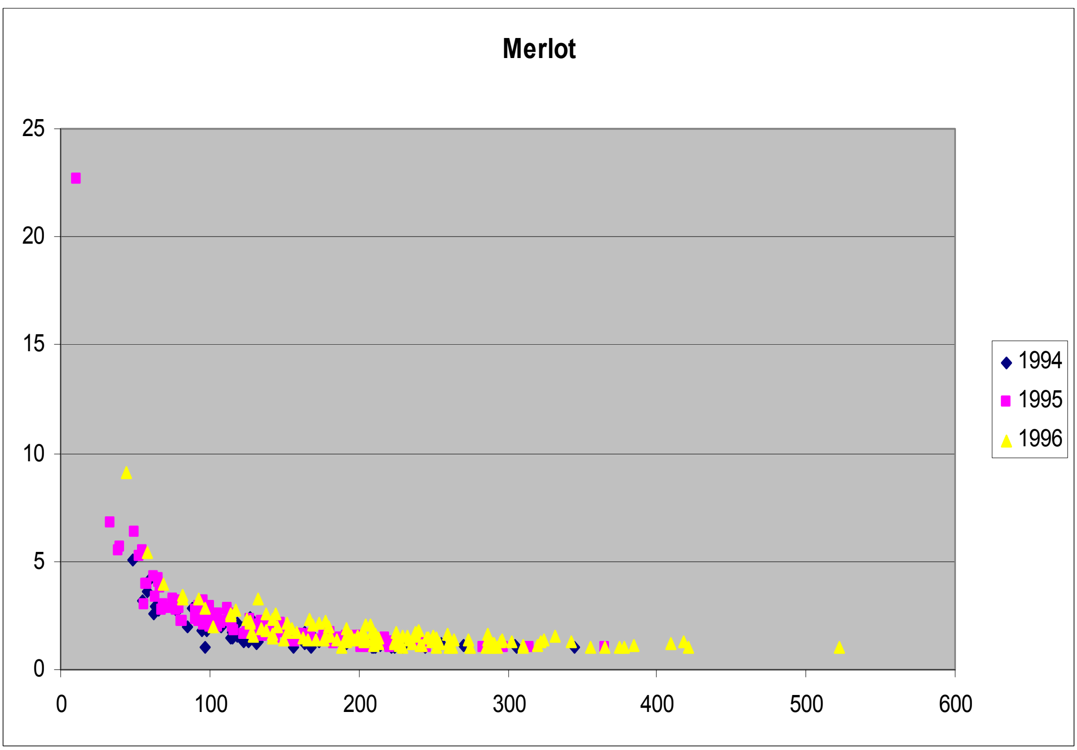


Figure 35. Quality quantity trade-off

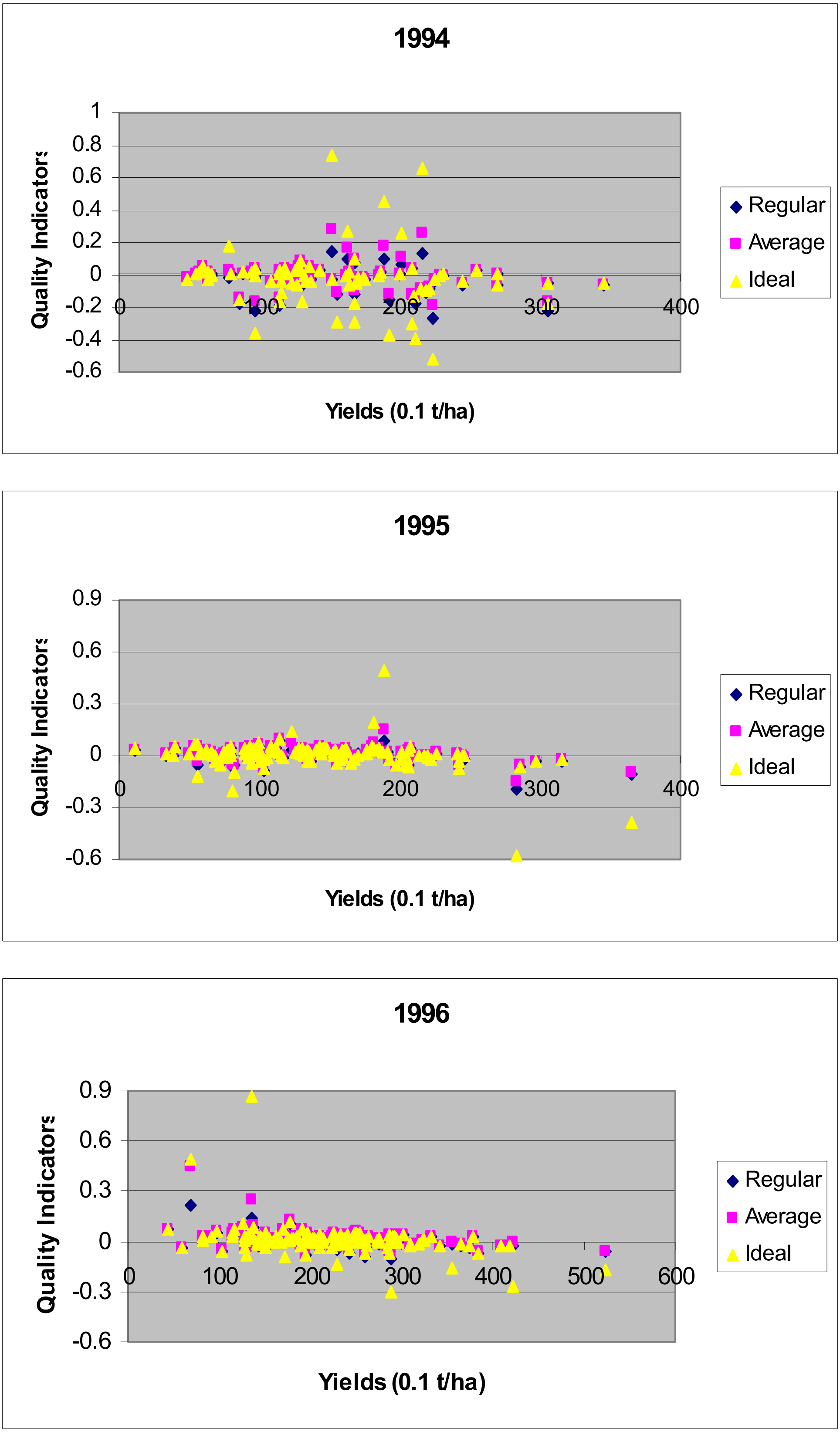


Figure 36. Quality Indicators vs. Yields: Merlot

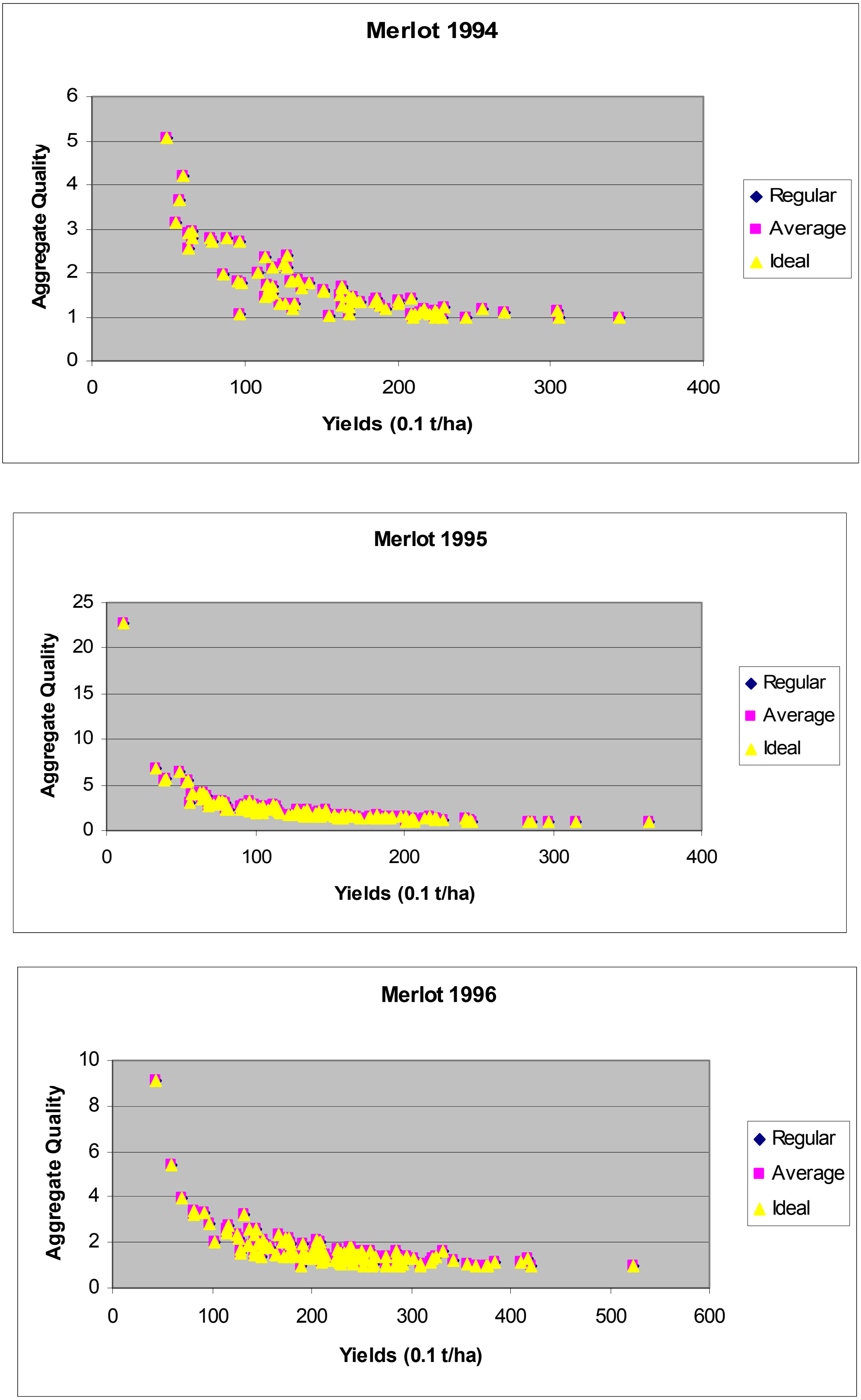


Figure 37. Aggregate Quality vs. Yields: Merlot