AN EVALUATION OF ALTERNATE FEED EFFICIENCY ESTIMATES IN BEEF CATTLE

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Abstract

In this paper the issue of nonlinearity and heterogeneity in the derivation of feed efficiency estimates for beef cattle based on performance data for 6253 animals is examined. Using parametric, non-parametric and integer programming approaches, we find evidence of nonlinearity between feed intake and measures of size and growth, and susceptibility of, feed efficiency estimates to assumptions pertaining to heterogeneity between animals and within cohorts. Further, differences in feed cost implied by selection based on different feed efficiency estimates were evaluated and compared-“costs of misspecification” of up to $280/kg DM was derived.

Key words: feed efficiency, beef cattle, feed costs, selection.

I. Introduction

Selection decisions in beef cattle have traditionally focused on expected progeny traits of high economic value. Recent innovations in livestock genome sequencing and increases in the availability of accurate individual animal feed intake data has allowed for the introduction of feed inputs into the construction of selection indices (Crews et al., 2006) used as the basis of selection decisions. This is significant for beef producers as improvements in feed efficiency are recognized as being critically linked to increased economic returns for the whole production system (Archer et al., 1999).

Residual feed intake (RFI), estimated as the difference between actual animal feed intake and predicted feed intake, has become a preferred measure of feed efficiency, across the different livestock production systems (Koch et al., 1963; Archer et al., 1999; Rauw et al., 2006). Differences in RFI capture variations in the efficiency with which individual animals utilize feed for maintenance and production; lower RFI values are more desirable (Johnson et al., 1999) since they imply more efficient conversion of feed into meat at lower costs. Empirically, predicted feed intake has been predominately estimated as a linear regression of actual animal feed intake on a set of covariates such as average daily gain (ADG), mid metabolic body weight (MBW) and measures of meat composition such as back fat (Hoque et al., 2009).

Previous analysis presents two important issues for further consideration. On one hand, the commonly used linear modeling of predicted feed intake is straightforward and the resultant efficiency estimates can be derived easily. On the other hand, in the presence of factors that induce heterogeneity across animals and nonlinearities between the covariates (such as ADG and MBW) and feed intake for a given animal, using a linear approach may result in inconsistent estimates. For beef cattle, where variation in production systems and treatments within a given system for a cohort of animals, is not uncommon, errors in the RFI prediction equation may distort the ranking of individual animal feed efficiency performance. Economically, this could imply the selection of less efficient cattle for breeding with resulting higher costs, and suboptimal selection of relatively more efficient animals. It is plausible that the distortions are more pronounced when dealing with animals drawn from the tails of the feed efficiency distribution. In an industry characterized by narrow profit margins, the potential impacts of these outcomes could be far-reaching (Richardson and Herd 2004). This notwithstanding, not much has been done in terms of evaluating the implications of parameter accuracy and consistency in RFI estimation.

The overall objective of this study is to evaluate the impact of the choice of empirical approach to estimating feed intake prediction equations for beef cattle on the ranking of animal feed performance. The specific objectives include i.) An assessment of beef cattle feed intake data for evidence of heterogeneity and nonlinearities ii.) An estimation of RFI using different empirical models and an assessment of the differences in efficiency rankings across the different estimation techniques used iii.) For a given cattle operation, an evaluation of the changes in costs to producers emanating from decisions based on the choice of specification used in the derivation of feed efficiency estimates.

To achieve the stated objectives, beef performance data for 6235 beef cattle raised in different research facilities in Canada between 1999-2012 is used. The particular geographical influences in addition to differences in breed, pen and year effects enhance the richness of the dataset in terms of diversity between animals and within cohorts. To exploit these unique features, both parametric and nonparametric approaches are implemented in the assessment of the data. The nonparametric models involve the application of localized regression and density estimation based on kernels. Local bivariate linear regression techniques are used in nonparametric regression analysis (Dinardo and Tobias 2001). Furthermore, parametric models include the use of hierarchical models. Although rarely used in the feed efficiency literature, the differences in treatment between animals and cohorts presents a nested design framework within which these multi-level models can be applied (Raudenbush 1993).

The contribution of this paper is two-fold; first, this paper contributes to existing studies in the agricultural economics literature that examine technical aspects of biological processes. For beef producers and practitioners in the livestock sector, this study makes the case for greater accuracy and empirical consistency in the estimation and derivation of estimates that form the basis for decisions with potentially significant economic consequences. In the light of current investments in livestock genome sequencing and inclusion of feed efficiency estimates in selection indices, the outcomes of this study could be timely.

The rest of the paper is organized as follows; Section II is a discussion of relevant literature. The empirical models estimated are specified in Section III. Section IV presents a discussion of results. Section V concludes the paper.

II. Literature Review

The consistency of an empirical approach may be evaluated in terms of functional forms used or consistency of the estimated parameters. In the production economics literature, these considerations typically extend beyond empirical appropriateness to economic implications of decisions based on incorrect empirical models (Havlicek et al., 1962). A significant proportion of the extant literature (Llewelyn and Featherson 1997: Frank et al., 1990) has focused on agronomic response functions with the cardinal considerations being the characteristics imposed as a result of assumed functional forms. For example, commonly used linear models have been criticized for a number of limitations. These include constraints on input substitution, the absence of growth plateaus amongst others (Ackello Ogutu et al., 1985). Frank et al., (1990) found differences of over 60% in optimal fertilizer application rates depending on the choice of functional form (GPW)-“cost of misspecification” of $48/acre was not uncommon.

Although similar to the agronomic sector in terms of the availability of large experimental datasets, little has been done in terms of assessing the economic implications of assumed empirical models used in the livestock sector. With recent innovations in genomic sequencing and the increasing emphasis on greater precision in animal selection, the issue of empirical consistency has gained increased importance. A critical application relates to the construction of feed efficiency indexes. For feed efficiency, the commonly used approach (e.g. Arthur et al., 2001; Herd and Bishop 2000 etc.) is to estimate residual feed intake (RFI) as residuals from the linear regression of feed intake on a set of standard covariates.

Initially proposed by Koch et al., (1963), RFI is defined as the difference between actual feed intake and predicted feed intake required for a given rate of gain and body weight. This residual portion of feed intake forms the basis for identifying relatively more efficient-cattle with lower (negative) RFIs. It has been suggested that RFI could represent variations in metabolic processes which determine feed efficiency (Brelin and Brannang 1982; Korver 1988). As errors from the regression of covariates that capture size and growth, residual feed intake is phenotypically independent of these production traitsArthur et al., (2001a) in a study of feed efficiency in Angus cattle, estimated a linear regression model of feed intake on metabolic weight and ADG controlling for group and sex effects. Residual feed intake was derived as the difference between an animal's actual feed intake and predicted feed intake given its' size and growth. Additionally, the study found evidence of genetic and phenotypic independence between RFI and component traits. This implies that selecting for RFI is unlikely to affect ADG and MWT, thus allowing for comparisons across cattle that differ with respect to these component traits.

Herd and Bishop (2000) assessed the existence of genetic variation in RFI in young bulls and the phenotypic and genotypic relationships between RFI and other important production traits such as mature cow size. The predicted feed equation was estimated as a linear regression of feed intake (FI) on MBW and ADG. RFI was derived as the residuals from the regression. Archer et al., 1999 estimated RFI as residuals from the linear regression of feed intake on ADG and MMWT. In an attempt to capture possible heterogeneity across animals resulting from gender and treatment, separate models were estimated for each gender within each test cohort. Arthur et al. (2001b) examined genetic and phenotypic relationships between different feed efficiency and growth measures in young Charolais bulls. Heterogeneity was constricted to year effects. In the case of Meyer et al., (2008), separate expected feed intake regression models were estimated for pregnant and open females in a classification of RFI in grazing beef cows.

Basarab et al., 2003 in a study using data from 176 steers, analyzed the relationship between residual feed intake, daily gain and other measures such as body size and composition. The study found evidence of the possibility of re-ranking cattle based on efficiency from the different linear models used (Basarab et al., 2003).

As evident from the literature, models used in RFI estimation are predominately linear and assumptions about heterogeneity have been largely unsystematic. In an industry where treatment effects, pen, trail and year effects vary widely across cohorts and between different levels of operations, assumptions about these effects can have a significant impact on the consistency of modeling procedures. Even more importantly, the incorporation of these estimates into selection indices brings to the fore the inter-temporal dimensions of the present issue. In other words, efficiency rankings based on incorrect empirical models may affect selection decisions that ultimately determine characteristics of future herds. For a trait such as feed efficiency that impacts significantly on profitability, these effects can be significant. Additionally, these potential impacts may further vary across the different sectors within the livestock industry as a result of differences in maintenance requirement. For example, an estimated 60-65% of feed in the mature cow herd is used to meet maintenance requirements suggesting considerable benefits from improved efficiency (Arthur et al., 2005).

A number of studies (e.g .Berry and Crowley 2013; Robinson 2005) have evaluated aspects of the assumptions underlying the derivation of RFI and its resultant properties. Perhaps the most stringent of these assumptions relates to nonlinearity between covariates and the modelling of diversity across animals. Indeed, on the issue of nonlinearity Berry and Crowley (2013) noted possible nonlinear relationships between feed intake and ADG and MWT amongst diverse populations and animals with inferior genetic merit for these traits. This notwithstanding, not much has been done in terms of evaluating the empirical models used in feed efficiency assessment and the likely economic implications for beef cattle operations. In this paper, parametric, nonparametric and integer programming approaches are used to analyze RFI estimates allowing for the effects of nonlinearity and heterogeneity. The parametric models involve the estimation of linear, quadratic, cubic and hierarchical models of actual animal feed intake on ADG and MWT under different heterogeneity assumptions. Residual feed intake estimates from these models are subsequently incorporated into a simple integer programming model that minimizes feed cost by selecting for the most feed efficient cattle.

III. Empirical Approach

Two empirical approaches i.e. nonparametric and parametric, are implemented in this paper. Nonparametric regressions are an extremely flexible method for exploring the relationship between two variables that does not impose any functional form on the relationship and allows the data to choose not only the parameter estimates but the shape of the curve or is this relationship itself (Deaton, 1997). For a dependent variable y_i (an indicator variable denoting a particular animal's feed intake) and explanatory variable x_i, (the animal's average daily gain, measured as kg/day), the usual regression function can be written as $y_i = m(x_i) + \xi_i$. The nonparametric regression estimator, also called the Naradaya Watson estimator, is defined as the local weighted average of the observations on the dependent variable (y) found in a band around the value of the explanatory variable (x), or, $\hat{m}(x) = \sum_{i=1}^{n} w_i(x_i) y_i$. Each w_i is calculated using a kernel estimator ($w_i(x_i) = (k(x - x_i)/h)/(\sum_i k(x - x_i)/h)$, where k(.) is the kernel function and h is the bandwidth around the point x in which the local average is calculated). In this sense the nonparametric regression estimator can be regarded as a sequence of conditional expectation estimates which when joined together can approximate a nonlinear function. In this paper, Naradaya Watson estimates are obtained from the regression of feed intake on the individual covariates (i.e. average daily gain and mid metabolic body weight).

In addition to the nonparametric analysis, parametric models are estimated using different functional forms and assumptions pertaining to the influence of contemporary group effects. The empirical approach is to specify commonly used linear regression models in addition to nonlinear and hierarchical models. Considering the nested design structure of the data, the latter models are used to analysis feed intake within treatments. Hierarchical models have been noted to be particularly suitable for regression analysis where the dependent variable is at the lowest level of disaggregation. For example in this study, a two-level hierarchy is assumed; feed intake by animal (level 1) within a specific treatment cohort (level 2). Further, the key consideration for these models relates to the variance structure; the identification of between and within cluster variance, the absence of independence in residuals and instances where composition of variance is of relevance (Snijders and Becker 2012; Cheng and Kelly 2011).

In line with Rabe-Hesketh and Skrondal (2008) the model for the feed intake DFI_{ij} of animal *i* under treatment *j* is specified as:

$$DFI_{ij} = B_1 + B_2 x_{2ij} + \ldots + B_s x_{sij} + \xi_{ij} \qquad (1)$$

$$\xi_{ij} \equiv \zeta_j + \varepsilon_{ij} \qquad (2)$$

where from equation (1) x_{2ij} through x_{sij} are covariates, and ξ_{ij}'s are the total residuals of the regression. Equation (2) is the error decomposition equation where ζ_j are treatment specific constant and ε_{ij} are animal specific error terms. These 2-level (i.e. animal and treatment) random intercept models are estimated for three i.e. linear, quadratic and cubic, functional forms. These models are denoted 7-9.

Further, linear and nonlinear functional forms are estimated under alternative assumptions of the presence or absence of heterogeneity in treatment for the different cohorts. The nonlinear functional forms estimated are quadratic and cubic functions. Equations 1-3 represent the specifications;

$$DFI_i = \beta_0 + \beta_1 ADG_i + \beta_2 MMWT_i + \varepsilon_i \qquad (3)$$

$$DFI_i = \beta_0 + \beta_1 ADG_i + \beta_2 MMWT_i + \beta_3 ADG_i \times MMWT_i + \beta_4 ADG_i^2 + \beta_5 MMWT_i^2 + \varepsilon_i \qquad (4)$$

$$DFI_i = \beta_0 + \beta_1 ADG_i + \beta_2 MMWT_i + \beta_3 ADG_i \times MMWT_i + \beta_4 ADG_i^2 + \beta_5 MMWT_i^2 + \beta_6 ADG_i^2 \times MMWT_i + \beta_7 MMWT_i^2 \times ADG_i + \beta_8 ADG_i^3 + \beta_9 MMWT_i^3 + \varepsilon_i \qquad (5)$$

For each animal *i*, DFI= actual feed intake, ADG= average daily gain, MMWT= mid metabolic body weight, the betas are regression coefficients, and ξ_i=residuals of the regression used as the measure of residual feed intake. Feed intake is recorded using an automated feeding system (see Basarab et al, 2003 for details of). Average daily gain is estimated from the linear regression of the animal's observed body weight (BW) on days on test (Wang et al. 2006; Basarab et al. 2007). Mid metabolic body weight is derived as the mean test period body weight raised to the 0.75 power for each animal (Arthur et al. 2001; Moore et al., 2008). This measure is used in lieu of actual weight in order to balance differences by animal in maintenance requirements resulting from differences in mature size (BIF 1986).

In total, six regression models are estimated using this approach. The first set of models (1-3) are estimated without controlling for heterogeneity i.e. pen/year/trail effects. These zero heterogeneity models enable us to assess the impact of heterogeneity on our modeling. Models 4-6 replicate the previous regression models (i.e. Equations 3-5); the only difference being the inclusion of contemporary group dummies capturing year/gender/pen effects between animals and within cohorts. In total, approximately 127 treatment effects were accounted for in these models. Refer to Appendix 1.

Residual feed intake from each model of the nine models is estimated as the difference between actual and predicted feed intake:

$$RFI_i = DFI_i - \hat{DFI}_i$$

For a given animal *i*, *RFI*=residual feed intake, DFI =actual feed intake, $\hat{DFI}$ =predicted feed intake.

To illustrate the potential importance of robustness of equation specification in farmer decision making, an integer programming model is formulated to evaluate the impact of the choice of animal based on feed efficiency estimate on the economics of a beef cattle operation. The specific case of the impact on feed costs is analyzed. In reality, a multiplicity of factors are considered in defining production objectives. The emphasis on feed cost in the present paper although narrow, allows for the implementation of a simple yet tractable framework for the evaluation of the direct impact of the choice of animal based on feed efficiency estimates on feed costs without the complexities of other competing objectives. Given that feed costs constitute the single most important cost in livestock production (Beckman et al. 2011), this approach seems justified. It is assumed that the producers' objective is to minimize the cost of feed/animal, i.e.:

$$\textit{Min}\ \text{Total Feed Cost(TC)} = N \times P(FC_i + RFI_{ai}) \qquad (4)$$

where N is number of cattle, P is feed price/head, FC_i presents feed intake, RFI denotes residual feed intake. The $i(i=1,2,3\ldots N)$ and $a(a=1,2,3\ldots 9)$ subscripts represent animal and methodology respectively. Thus RFI_{11} represents RFI derived from methodology 1 for animal 1. For the present analysis, feed price describe is assumed to be CAN$260/tonne[1] which translates to $0.26/kg. Assuming 90% dry matter (DM), feed price/Kg DM is equivalent to CAN$0.234kg/DM. Depending on prices of substitute feed grains and supply conditions, feed wheat is incorporated in beef rations replacing portions of corn and barley (Saskatchewan Forage Council 2011).

The impact of the choice of animals for beef production based on RFI estimates on three alternative beef cattle operations differing by size is analyzed. The case considered is one of a single time horizon. The optimization goal i.e. the selection of the cost minimizing N in equation (4) is assessed for selection of top 5, 10 and 20% efficient beef cattle from the total sample of animals. It is assumed that producers have information on estimates of feed efficiency ex–ante and select from the pool of animals based on these estimates.

Data and Data Sources

Data was collated from three research projects. It comprises performance data collected by; the Agriculture and Agri-Food Canada (AAFC) for the Phenomic Gap project (PG1), the University

[1] We use the current feed price in Lethbridge AB published by the Alberta Canola Producers Commission.

of Alberta at the Kinsella ranch (KIN) and the University of Guelph at the Elora test station (UOG).

The PG1 dataset, consisted of animal performance tested (i.e. measure for feed intake concurrently with growth rate and body composition) between 2003 and 2012 at the AAFC research station at Lacombe, Olds College, and three other commercial feedlots all in Alberta. Sire breeds were Angus (AN), Charolais (CH), Gelbveih (GV) and Beefbooster (BR). Average age at the start of test was 311 days. The test period, preceded by 28-24day adjustment period spanned 108-113days.

Data on cattle within the KIN data was collected over the period 2007-2011. These steers were Angus, Charolaias sired or sired by the University of Alberta hybrid bulls with a composite dam line. Average age at the start of test was 222 days.

The UOG dataset comprised Angus, Charolais, Limousin, Piedmontese and Simmental sired animals that were performance tested between 1999 and 2007. Animals typically 200 days old were performance tested at the Elora Beef Research center (EBRC) after a 28-35 day adaptation period. A detailed description of the data and methods can be found in Basarab et al. (2011); Durunna et al., (2011); Lu et al., (2013).

Measures of feed intake growth rate and body composition i.e. feed intake (kg/day), mid-metabolic body weight (kg) and average daily gain (ADG) for the 6253 animals were used in this study. Additionally, two types (i.e. main and subgroup) of contemporary group effects are modelled in this study. The main group effects CG1, CG2 and CG3 are used to denote the 3 main sources of the dataset i.e. KIN, PG1 and UOG respectively. The sub contemporary group effects are defined as pen, year, animal type etc. effects for the relevant cohorts and these are captured as dummy variables. Table 1 is a summary of the data.

IV Results and Discussion

Tables 1a and b. capture descriptive statistics of DFI, MMWT and ADG for the overall sample (1a) and the main contemporary groups (1b). Mean feed intake for the entire sample is approximately 9.28kg/day, over the range of 0.8kg/day (min) and 19.41kg/day (max). Mean MMWT and ADG were 94.08kg and 1.52kg/day respectively.

Insert table 1a. here.

Across contemporary groups, mean values DFI, MMWT and ADG from CG1 tended to be generally lower relative to the overall sample, whilst estimates for CG3 were higher. Mean values for contemporary group 2 were 9.06kg/day, 95.72kg and 1.46kg/day for DFI, MMWT and ADG respectively.

Insert table 1b. here.

Regression Results: Zero Heterogeneity Models.

Nonparametric Assessment

The results of the bivariate analysis are captured by Figures 1-6. Feed intake is captured on the ordinate axes whilst the covariates are plotted on the abscissa. The resulting differences in the results across the three main treatment groups are indicative of heterogeneity in treatment. Evidence of nonlinearity particularly in the relation between feed intake and ADG in contemporary group 1, and between feed intake and MMWT in contemporary group 3 are also observable.

Insert figure 1 here.

Insert figure 2 here.

Insert figure 3 here.

Insert figure 4 here.

Insert figure 5 here.

Insert figure 6 here.

Parametric Estimation

The non-parametric models estimated in the previous section are complemented with the estimation of parametric models. The first set of models (Tables 2) were estimated under the assumption of zero heterogeneity in treatment. In essence, these models are the base models that allow for the evaluation of treatment effects when these effects are subsequently incorporated.

A priori, ADG and MMWT were expected to have be positively related to feed intake. From the OLS regression results, the parameter estimates of model 1 are consistent with a priori expectations. A unit increase in average daily gain, increases feed intake by 0.734. Mid metabolic body weight also has a positive effect on daily feed intake; cattle with higher weights have higher feed intakes. From the quadratic and cubic specifications, parameter estimates from the relatively more complex specifications do not seem to significantly improve model fit. R-squared estimates increase marginally as compared to the linear case. Residual feed intake denoted as RFI1, RFI2 and RFI3 were derived as residuals from models 1, 2 and 3 respectively. Summary statistics of the estimated RFI values are presented in Table 5.

Insert table 2 here.

Regression Model: Controlling for Heterogeneity

The models estimated in this section were estimated controlling for heterogeneity across animals in a given cohort and across cohorts in a given treatment. These effects were namely, year/pen/treatment effects. A hundred and twenty-seven dummy variables[2] were included in this set of regression models. Due to the large number of treatment effects, reported results are restricted to the main variables.

[2] Where 1 denoted the presence of a given effect, zero otherwise.

From Table 3, Model 4 is identical to Model 1, the only difference being that the latter models account for treatment effects. Aside from the change in sign of the intercept term, a significance difference between the two models is the increased coefficient on average daily gain. Additionally the R-squared estimate is approximately 0.82 suggesting an increment in model fit relative to the base scenario (Table 2).

Insert table 3 here.

Additionally, the nonlinear models (i.e. models 5 and 6) estimated under the assumption of heterogeneity in treatments tended to have higher R-squared values. Unlike model 2, the sign of the coefficient of ADG in model 4 is significant and consistent with prior expectations. With the exception of the squared MMWT coefficient, all the parameters estimated are significantly greater than zero. Model 6 shows parameter estimates for the cubic functional form. As evident from the R-squared estimates, model fit does not seem to improve significantly between specifications under a given assumption.

Table 4, is a summary of estimation results of the hierarchical model and the associated likelihood ratio estimates. Linear and nonlinear specifications identical to those of the previous sections were estimated. In terms of estimated parameter magnitudes, these models tend to be similar to the models estimated in the absence of treatment effects (Models 1-3).This implies that treatments effects are higher within groups than between groups for a given animal. Residual feed intake (RFI) 1-9 are the corresponding residuals of the regression models estimated.

Insert table 4 here.

Descriptive statistics of the different estimates of residual feed intake derived from the regression models are summarized in Table 5. As expected, RFI across the different specifications and assumptions have a mean of zero. Residual feed intake values ranged from a maximum of 12.29 to a minimum of 6.22. As observed from the parametric model estimates, the RFI values from the multi-level model (RFI7-9) are identical to the set of models estimated under the zero heterogeneity assumptions (RFI1-3) suggesting heterogeneity is more produced within the sub-treatments. Accounting for the treatment effects seems to reduce variance with the RFI estimates indicating improved model fit. The higher standard deviations in the zero heterogeneity models are indicative of a wider dispersion in distribution of these feed efficiency values. Residual feed intake estimates under a specific set of assumptions generally tend to be identical as evident from the observable similarities in RFIs 1-3, 4-6 and 7-9.

Insert table 5 here.

DENSITY PLOTS OF RFI ESTIMATES

The kernel density plots are used to draw parallels in the distribution of the feed efficiency estimates under the different underlying assumptions. Consistent with the summary data in Table

5, the density plots of feed efficiency estimates for heterogeneity models tended to have a lower variance compared to the zero heterogeneity models which also had wider tails. For selection decisions these patterns could be significant as the tails of the distribution are a critical consideration. For example from Figures 7-9, cattle selected on the basis of different estimates may differ as evident from the differences in the distribution of the density functions. For a given assumption, the choice of functional form does not seem to alter the distribution of the density function (Figures 10 and 11).

Insert figure 7 here.

Insert figure 8 here.

Insert figure 9 here.

Insert figure 10 here.

Insert figure 11 here.

Cattle are classified into three categories (high, moderate and least efficient) based on RFI values. These categorizations were based on the relevant animals RFI being < 0.5 stand deviations from the mean (low RFI group), >0.5 standard deviations from the mean (high RFI group) and ±0.5 standard deviations from the mean (medium RFI group). Results of the classification support the patterns observed in the density function estimates-key result being that zero heterogeneity models tended to wider at the lower tails. The number of cattle under a given assumption tended to be fairly robust across the different specifications. For example, the difference between RFI1 and RFI4 for cattle in the high efficient category was approximately 400 animals. Depending on the size of the operation, the impact of these assumptions on feed cost may be significant. Assuming the specifications that incorporate heterogeneity are ideal, selecting for efficiency based no heterogeneity models over-selects, possibly including inefficient cattle. Within the zero heterogeneity models differences in the number of animals were marginal.

Insert table 6 here.

IMPACT OF RFI ESTIMATES ON SELECTION OUTCOMES

The possible incorporation of the RFI estimates into selection indices links parametric choices to economic outcomes. The previous analysis is extended to examine the economic implications of selection based on the different functional forms and the corresponding RFIs. Tables 7-9 are a summary of results from the integer programming model and the changes in cost emanating from different selection strategies. Strategies considered were namely; selecting top 5% (table 7), 10%

(table 8) and 20% (table 9) efficient cattle. This implies that the relevant size of operation[3] examined were approximately 320, 630 and 1250 animals respectively.

Insert table 7 here.

Insert table 8 here.

From the analysis, estimates of the cost of misspecification range from CAN$0.09 kg/DM to CAN$280 /Kg DM. For a given operation these changes in cost tend to be marginal within a given set of assumptions. For example, From Table 7, selecting based on RFI 1-3 (zero heterogeneity models) when the true model is RFI1 resulted in marginal changes in cost of up to CAN$1.03/kg DM. These differences are more pronounced across models particularly for zero treatment vis-a-vis treatment effect models. Additionally, the cost implications of selection based on the wrong empirical models increases with scale as evident from the increases observable at the 20% selection level.

Insert table 9 here.

V. Conclusion

Results from both the parametric and nonparametric analysis are indicative of possible nonlinearity between feed intake and ADG and MMWT. Additionally, we also found evidence of substantial susceptibility of feed efficiency estimates to assumptions made in terms heterogeneity between animals and within cohorts for a given sample. Indeed our results indicate that depending on the empirical approach used selecting above or below the optimal number of animals may likely occur resulting in significant economic impacts. From the integer programming model, “cost of misspecification” of up to $280/kg DM ($311/kg as fed) was derived. Further, these costs were found to be increasing in scale.

In light of the ongoing investments in genomic improvement particularly with respect to the inclusion of feed efficiency in traditional selection indices, the findings of this study may be crucial. Firstly, it brings to the fore the need for more careful consideration of the issue of empirical consistency in the assessment of animal performance data-especially when decision based on these models have intertemporal and scale implications. For beef cattle production where the impact of factors such as year, breed, pen, sex, treatment etc differ widely, more systematic modeling and greater rigour in the data assessment process remains imperative.

Possible extensions of this study could be a consideration of the intertemporal dimensions of the present issue within a multi-goal integer programming framework. With the established linkages between feed efficiency and environmental sustainability through the reduced carbon footprint nexus, the extension of the present analysis to include environment impacts would be worthwhile.

[3] 5, 10 and 20% of 6253 animals.

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Appendix 1

SUMMARY OF SUBCONTEMPORARY GROUPS (SCG)

SCG	Obs	Mean Std. Dev.	Min	Max
kin_1	6253	.0131137 .1137708	0	1
kin_1_b	6253	.0273469 .1631051	0	1
kin_2	6253	.0099152 .0990883	0	1
kin_2_b	6253	.0134336 .1151313	0	1
kin_2c_c	6253	.0140732 .1178024	0	1
kin_3	6253	.0118343 .1081487	0	1
kin_3_b	6253	.0115145 .1066945	0	1
kin_3c_d	6253	.0115145 .1066945	0	1
kin_4	6253	.0107149 .1029648	0	1
kin_5	6253	.012474 .1109972	0	1
kin_6	6253	.0116744 .1074242	0	1
pg1_1	6253	.0046378 .0679485	0	1
pg1_2	6253	.0067168 .0816868	0	1
pg1_3	6253	.0030385 .0550436	0	1
pg1_4	6253	.0070366 .0835956	0	1
pg1_5	6253	.0070366 .0835956	0	1
pg1_6	6253	.0070366 .0835956	0	1
pg1_71	6253	.0044779 .0667721	0	1
pg1_72	6253	.0044779 .0667721	0	1
pg1_81	6253	.0046378 .0679485	0	1
pg1_82	6253	.0043179 .0655742	0	1
pg1_91	6253	.0044779 .0667721	0	1
pg1_92	6253	.0044779	0	1

		.0667721		

CG=contemporary group

SCG	Obs	Mean Std. Dev.	Min	Max
pg1_101	6253	.0043179 .0655742	0	1
pg1_102	6253	.0044779 .0667721	0	1
pg1_11	6253	.0177515 .1320574	0	1
pg1_12	6253	.0033584 .0578588	0	1
pg1_13	6253	.0031985 .056469	0	1
pg1_14	6253	.0097553 .0982939	0	1
pg1_15	6253	.0108748 .1037219	0	1
pg1_16	6253	.0097553 .0982939	0	1
pg1_17	6253	.0113545 .1059595	0	1
pg1_18	6253	.0033584 .0578588	0	1
pg1_19	6253	.0150328 .1216929	0	1
pg1_20	6253	.0116744 .1074242	0	1
pg1_21	6253	.0110347 .1044734	0	1
pg1_22	6253	.0107149 .1029648	0	1
pg1_23	6253	.0105549 .1022017	0	1
pg1_24	6253	.0097553 .0982939	0	1
pg1_25	6253	.0075164 .0863776	0	1
pg1_26	6253	.0071965 .0845334	0	1
pg1_27	6253	.006237 .0787343	0	1
pg1_28	6253	.0095954 .0974928	0	1
pg1_29	6253	.0073565 .0854606	0	1
pg1_30	6253	.0076763 .0872846	0	1

SCG	Obs	Mean Std. Dev.	Min	Max
pg1_31	6253	.0156725 .1242148	0	1
pg1_32	6253	.0156725 .1242148	0	1
pg1_33	6253	.0180713 .1792846	0	1
pg1_34	6253	.0179114 .1326401	0	1
pg1_35	6253	.0150328 .1216929	0	1
pg1_36	6253	.0148729 .1210537	0	1
pg1_37	6253	.0215896 .145351	0	1
pg1_38	6253	.0190309 .1366443	0	1
pg1_39	6253	.0223893 .1479577	0	1
pg1_40	6253	.0225492 .148473	0	1
pg1_41	6253	.016632 .1278984	0	1
pg1_42	6253	.0131137 .1137708	0	1
pg1_43	6253	.0239885 .1530254	0	1
pg1_44	6253	.0139133 .1171407	0	1
pg1_46	6253	.0065569 .0807149	0	1
pg1_48	6253	.0158324 .1248368	0	1
pg1_49	6253	.0067168 .0816868	0	1
pg1_50	6253	.0231889 .150515	0	1
uof_null	6253	.0036782 .0605416	0	1
uof_1_1	6253	.0019191 .0437687	0	1
uof_2_1	6253	.0038382 .0618388	0	1
uof_2_2	6253	.0036782 .0605416	0	1
uof_3_2	6253	.0003198 .0178828	0	1
uof_4_1	6253	.006237	0	1

		.0787343		
SCG	Obs	Mean	Min	Max
uof_5_1	6253	.0057572 .0756638	0	1
uof_6_1	6253	.004158 .0643535	0	1
uof_6_2	6253	.0019191 .0437687	0	1
uof_6_3	6253	.002079 .0455523	0	1
uof_6_4	6253	.0017592 .0419087	0	1
uof_6_5	6253	.0022389 .0472681	0	1
uof_6_6	6253	.0011195 .0334423	0	1
uof_7_1	6253	.0030385 .0550436	0	1
uof_7_2	6253	.0036782 .0605416	0	1
uof_7_3	6253	.0030385 .0550436	0	1
uof_9_1	6253	.002079 .0455523	0	1
uof_10_1	6253	.0022389 .0472681	0	1
uof_10_2	6253	.0027187 .0520743	0	1
uof_10_3	6253	.0023988 .0489232	0	1
uof_11_1	6253	.002079 .0455523	0	1
uof_11_2	6253	.0004798 .0219001	0	1
uof_11_3	6253	.0001599 .0126461	0	1
uof_11_4	6253	.0007996 .0282684	0	1
uof_11_5	6253	.0004798 .0219001	0	1
uof_12_1	6253	.0009595 .030964	0	1
uof_13_1	6253	.0076763 .0872846	0	1

SCG	Obs	Mean Std. Dev.	Min	Max
uof_15_1	6253	.006237 .0787343	0	1
uof_16_1	6253	.0031985 .056469	0	1
uof_17_1	6253	.0073565 .0854606	0	1
uof_17_2	6253	.0019191 .0437687	0	1
uof_17_3	6253	.0017592 .0419087	0	1
uof_17_5	6253	.0019191 .0437687	0	1
uof_19_1	6253	.0068767 .0826469	0	1
uof_20_1	6253	.0033584 .0578588	0	1
uof_21_1	6253	.0068767 .0826469	0	1
uof_22_1	6253	.0055973 .0746115	0	1
uof_23_1	6253	.0001599 .0126461	0	1
uof_25_1	6253	.0052775 .07246	0	1
uof_26_1	6253	.0033584 .0578588	0	1
uof_26_2	6253	.0025588 .0505236	0	1
uof_26_3	6253	.0030385 .0550436	0	1
uof_27_1	6253	.0033584 .0578588	0	1
uof_28_1	6253	.004158 .0643535	0	1
uof_28_2	6253	.0014393 .0379139	0	1
uof_28_3	6253	.0031985 .056469	0	1
uof_28_4	6253	.0025588 .0505236	0	1
uof_29_1	6253	.0004798 .0219001	0	1
uof_30_1	6253	.0030385 .0550436	0	1
uof_30_2	6253	.0028786 .0535798	0	1

CG	Obs	Mean	Min	Max
uof_30_3	6253	.0030385 .0550436	0	1
uof_30_4	6253	.0030385 .0550436	0	1
uof_30_5	6253	.0027187 .0520743	0	1
uof_30_6	6253	.0028786 .0535798	0	1
uof_30_7	6253	.0014393 .0379139	0	1
var122	6253	.0015992 .0399616	0	1
uof_31_1	6253	.0036782 .0605416	0	1
uof_32_1	6253	.0107149 .1029648	0	1
uof_34_1	6253	.0009595 .030964	0	1
uof_34_2	6253	.0007996 .0282684	0	1
uof_34_3	6253	.0001599 .0126461	0	1
uof_34_4	6253	.0012794 .0357485	0	1
uof_34_5	6253	.0011195 .0334423	0	1
uof_35_1	6253	.0070366 .0835956	0	1
uof_34_6	6253	.0007996 .0282684	0	1
uof_36_1	6253	.0052775 .07246	0	1
uof_37_1	6253	.0019191 .0437687	0	1
uof_39_1	6253	.0057572 .0756638	0	1
uof_40_1	6253	.0028786 .0535798	0	1
uof_40_2	6253	.0028786 .0535798	0	1
uof_40_3	6253	.0031985 .056469	0	1
uof_40_4	6253	.0031985 .056469	0	1

SCG	Obs	Mean Std. Dev.	Min	Max
uof_40_5	6253	.0006397 .0252861	0	1
uof_40_6	6253	.0023988 .0489232	0	1
uof_40_7	6253	.002079 .0455523	0	1
uof_40_8	6253	.0003198 .0178828	0	1
uof_40_9	6253	.0011195 .0334423	0	1
uof_41_1	6253	.0017592 .0419087	0	1
uof_41_2	6253	.0015992 .0399616	0	1
uof_41_3	6253	.0017592 .0419087	0	1
uof_41_4	6253	.0019191 .0437687	0	1
uof_41_5	6253	.0017592 .0419087	0	1
uof_41_6	6253	.0014393 .0379139	0	1
uof_41_7	6253	.0025588 .0505236	0	1
uof_41_8	6253	.002079 .0455523	0	1
uof_41_9	6253	.0017592 .0419087	0	1
uof_41_10	6253	.0017592 .0419087	0	1
uof_41_11	6253	.0017592 .0419087	0	1
uof_41_12	6253	.0015992 .0399616	0	1
var156	6253	.0001599 .0126461	0	1
uof_43_1	6253	.0043179 .0655742	0	1
uof_44_1	6253	.0019191 .0437687	0	1
uof_47_1	6253	.0161522 .126071	0	1
uof_48_1	6253	.0049576 .0702412	0	1
uof_49_1	6253	.0055973 .0746115	0	1
uof_49_2	6253	.0038382 .0618388	0	1

List of Tables

Table 1a: Summary Statistics for Data

	DFI*(kg/d)	MMWT(kg)	ADG(kg/d)
Obs.	6253	6253	6253
Mean	9.28	94.08	1.52
Std. Dev	1.97	14.21	0.43
Minimum	0.87	48.84	-0.70
Maximum	19.41	159.17	3.30

*DFI= feed intake; MMWT=mid metabolic body weight; ADG=average daily gain. Data also included 3 main contemporary groups and 127 sub contemporary groups captured with dummy variables.

TABLE 1b : DESCRIPTIVE STATISTICS FOR EACH CONTEMPORARY GROUP

	CG 1			CG 2			CG 3		
	DFI (kg/d)	MMWT (kg)	ADG (kg/d)	DFI (kg/d)	MMWT (kg)	ADG (kg/d)	DFI (kg/d)	MMWT (kg)	ADG (kg/d)
Obs.	923	923	923	3572	3572	3572	1758	1758	1758
Mean	8.98	81.87	1.37	9.06	95.72	1.46	9.89	97.17	1.71
Std. Dev.	1.87	11.36	0.26	1.92	12.73	0.42	1.98	15.11	0.43
Min	4.75	57.69	0.71	4.07	60.02	-0.70	0.87	48.84	0.24
Max	14.54	114.77	2.33	17.69	145.22	2.94	19.41	159.17	3.30

CG=Contemporary Group

Table 2: Estimates of zero heterogeneity models

Variable*	MODEL1 Coefficient	MODEL2 Coefficient	MODEL3 Coefficient
Intercept	1.418392***	3.560845***	14.87186***
ADG	.7340613***	-.483858	-.1223198
MMWT	.0717519***	.0454941***	-.3160894***
ADG*MMWT		.0150061***	-.0017078
ADG^2		-.0840896	.2683189
$MMWT^2$		.0000218***	.0038441***
$MMWT^2$*ADG			.0001104
ADG^2*MMWT			-.001923
ADG^3			-.0396345
$MMWT^3$			-.0000133***
R^2	0.3765	0.3791	
Adjusted R^2	0.3763	0.3786	
F-statistic	1887.43	762.94	
Prob(F-statistic)	0.0000	0.0000	

*, ** and *** represent 0.10, 0.05 and 0.01 levels of statistical significance respectively.

Table 3: Estimates controlling for treatments

Variable*	MODEL4 Coefficient	MODEL5 Coefficient	MODEL6 Coefficient
Intercept	-.5214189***	-2.46004***	-3.726067**
ADG	1.412954***	2.723962***	5.391204**
MMWT	.0751022***	.0950957***	.0954506*
ADG*MMWT		-.0095341***	-.028321
ADG^2		-.1162257*	-1.265279***
$MMWT^2$		-.0000276	.0001108
$MMWT^2$*ADG			-.0000801
ADG^2*MMWT			.0116777****
ADG^3			-.0110311
$MMWT^3$			-1.32e-07
R^2	0.8270	0.8281	0.8285
Adjusted R^2	0.8224	0.8235	0.8237
F-statistic	180.84	178.84	174.89
Prob(F-statistic)	0.000	0.0000	0.0000

*, ** and *** represent 0.10, 0.05 and 0.01 levels of statistical significance respectively.

Table 4: Estimates of Hierarchical models

Variable*	MODEL7 Coefficient	MODEL8 Coefficient	MODEL9 Coefficient
Intercept	.985378***	-.0900854	8.577031***
ADG	.5205706***	-1.677015***	-2.763583
MMWT	.0822786***	.139178***	-.1170352
ADG*MMWT		.0232251***	.0185453
ADG^2		-.0387219	.8941247
$MMWT^2$		-.0004657***	.0021755**
$MMWT^2$*ADG			.00012
ADG^2*MMWT			-.006974
ADG^3			-.0479946
$MMWT^3$			-9.29e-06**
Log Likelihood	-11429.98	-11406.952	-11400.642
Wald chi2	4046.18	4122.72	4143.65
Prob (Chi2)	0.0000	0.0000	0.0000

*, ** and *** represent 0.10, 0.05 and 0.01 levels of statistical significance respectively.

Table 5: Summary statistics RFI

	RFI 1	RFI 2	RFI 3	RFI 4	RFI 5	RFI 6	RFI 7	RFI 8	RFI 9
Obs.	6253	6253	6253	6253	6253	6253	6253	6253	6253
Mean	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Std. Dev	1.553	1.549	1.547	.818	.815	.814	1.503	1.498	1.496
Min	-7.919	-7.885	-7.836	-8.768	-8.880	-8.936	-8.134	-8.150	-8.104
Max	12.236	12.117	11.983	6.231	6.247	6.215	12.176	12.293	12.211

Table 6: Classification of cattle based on RFI estimates

	HIGH EFFICENT	MODERATE EFFICIENT	LEAST EFFICIENT	TOTAL
RFI1	1924	2828	1501	6253
RFI2	1929	2803	1521	6253
RFI3	1932	2815	1506	6253
RFI4	1562	3116	1575	6253
RFI5	1555	3146	1552	6253
RFI6	1563	3119	1571	6253
RFI7	1910	2762	1581	6253
RFI8	1936	2742	1575	6253
RFI9	1939	2741	1573	6253

TABLE 7. OPTIMAL COSTS ($) AND RELATIVE COST OF MISSPECIFCATION (5% SELECTION)

"TRUE" RFI ESTIMATE	OPTIMAL ? COSTS COST/KG/DM	COST DIFFERENCES INCURRED BY SELECTING CATTLE BASED ON								
		RFI1	RFI2	RFI3	RFI4	RFI5	RFI6	RFI7	RFI8	RFI9
RFI1	487.36	0.00	1.23	-0.09	-64.86	-65.86	-65.87	2.39	2.07	1.33
RFI2	486.13	-1.23	0.00	-1.32	-66.09	-67.09	-67.10	1.16	0.84	0.10
RFI3	487.45	0.09	1.32	0.00	-64.77	-65.77	-65.78	2.48	2.16	1.42
RFI4	552.22	64.86	66.09	64.77	0.00	-1.00	-1.01	67.25	66.93	66.19
RFI5	553.22	65.86	67.09	65.77	1.00	0.00	-0.01	68.25	67.93	67.19
RFI6	553.23	65.87	67.10	65.78	1.01	0.01	0.00	68.26	67.94	67.2
RFI7	484.97	-2.39	-1.16	-2.48	-67.25	-68.25	-68.26	0.00	-0.32	-1.06
RFI8	485.29	-2.07	-0.84	-2.16	-66.93	-67.93	-67.94	0.32	0.00	-0.74
RFI9	486.03	-1.33	-0.10	-1.42	-66.19	-67.19	-67.2	1.06	0.74	0.00

Number of cattle=320

TABLE 8: OPTIMAL COSTS($) AND RELATIVE COST OF MISPECIFCATION (10% selection)

"TRUE" RFI ESTIMATE	OPTIMAL COSTS COST/KG/DM	CHANGE IN COST INCURRED BY SELECTING CATTLE BASED ON								
		RFI1	RFI2	RFI3	RFI4	RFI5	RFI6	RFI7	RFI8	RFI9
RFI1	1021.50	0.00	1.05	-1.34	-132.2	-133.71	-133.82	-4.32	-4.98	-5.83
RFI2	1020.45	-1.05	0.00	-2.39	-133.25	-134.76	-134.87	-5.37	-6.03	-6.88
RFI3	1022.84	1.34	2.39	0.00	-130.86	-132.37	-132.48	-2.98	-3.64	-4.49
RFI4	1153.70	132.2	133.25	130.86	0.00	-1.51	-1.62	127.88	127.22	126.37
RFI5	1155.21	133.71	134.76	132.37	1.51	0.00	-0.11	129.39	128.73	127.88
RFI6	1155.32	133.82	134.87	132.48	1.62	0.11	0.00	129.5	128.84	127.99
RFI7	1025.82	4.32	5.37	2.98	-127.88	-129.39	-129.5	0.00	-0.66	-1.51
RFI8	1026.48	4.98	6.03	3.64	-127.22	-128.73	-128.84	0.66	0.00	-0.85
RFI9	1027.33	5.83	6.88	4.49	-126.37	-127.88	-127.99	1.51	0.85	0.00

Number of cattle=630

TABLE 9 OPTIMAL COST($) AND RELATIVE COST OF MISPECIFCATION (20% selection)

"TRUE" RFI ESTIMATE	OPTIMAL COSTS COST/KG/DM	CHANGE IN COST INCURRED BY SELECTING CATTLE BASED ON								
		RFI1	RFI2	RFI3	RFI4	RFI5	RFI6	RFI7	RFI8	RFI9
RFI1	2157.42	0.00	0.27	-3.2	-246.45	-247.81	-247.95	-19.86	-19.26	-20.88
RFI2	2157.15	-0.27	0.00	-3.47	-246.72	-248.08	-248.22	-20.13	-19.53	-21.15
RFI3	2160.62	3.20	3.47	0.00	-243.25	-244.61	-244.75	-16.66	-16.06	-17.68
RFI4	2403.87	246.45	246.72	243.25	0.00	-1.36	-1.499	226.59	227.19	225.57
RFI5	2405.23	247.81	248.08	244.61	1.36	0.00	-0.139	227.95	228.55	226.93
RFI6	2405.36	247.95	248.23	244.75	1.50	0.139	0.00	228.09	228.69	227.07
RFI7	2177.28	19.86	20.13	16.66	-226.59	-227.95	-228.09	0.00	0.60	-1.02
RFI8	2176.68	19.26	19.53	16.06	-227.19	-228.55	-228.69	-0.6	0.00	-1.62
RFI9	2178.30	20.88	21.15	17.68	-225.57	-226.93	-227.07	1.02	1.62	0.00

Number of cattle=1250

LIST OF FIGURES

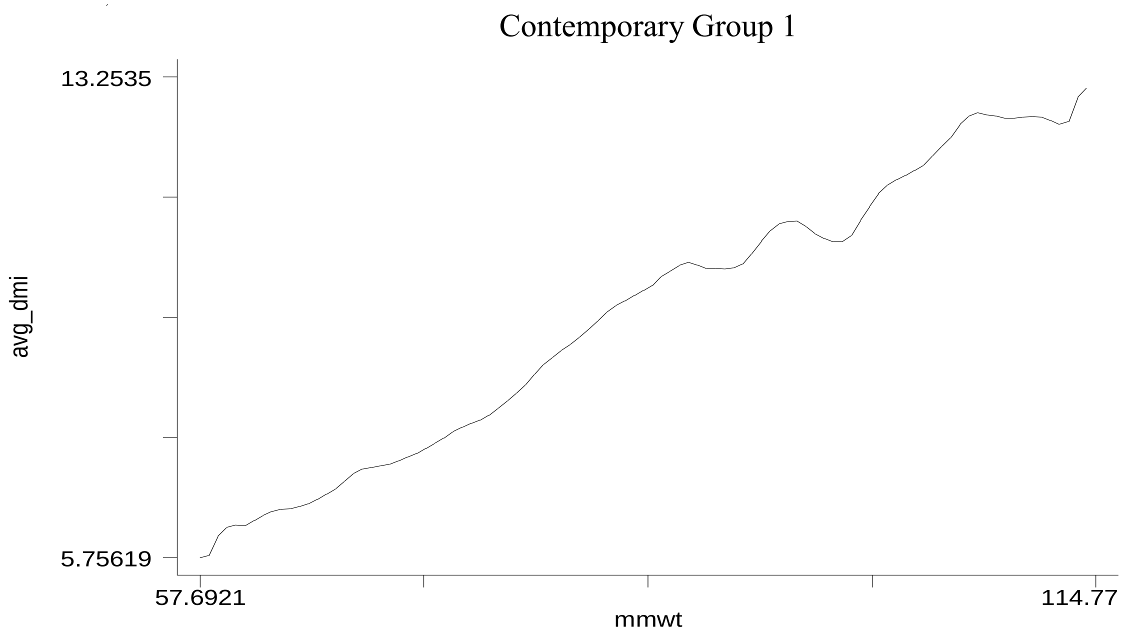

Figure 1: Feed intake-mid metabolic body weight

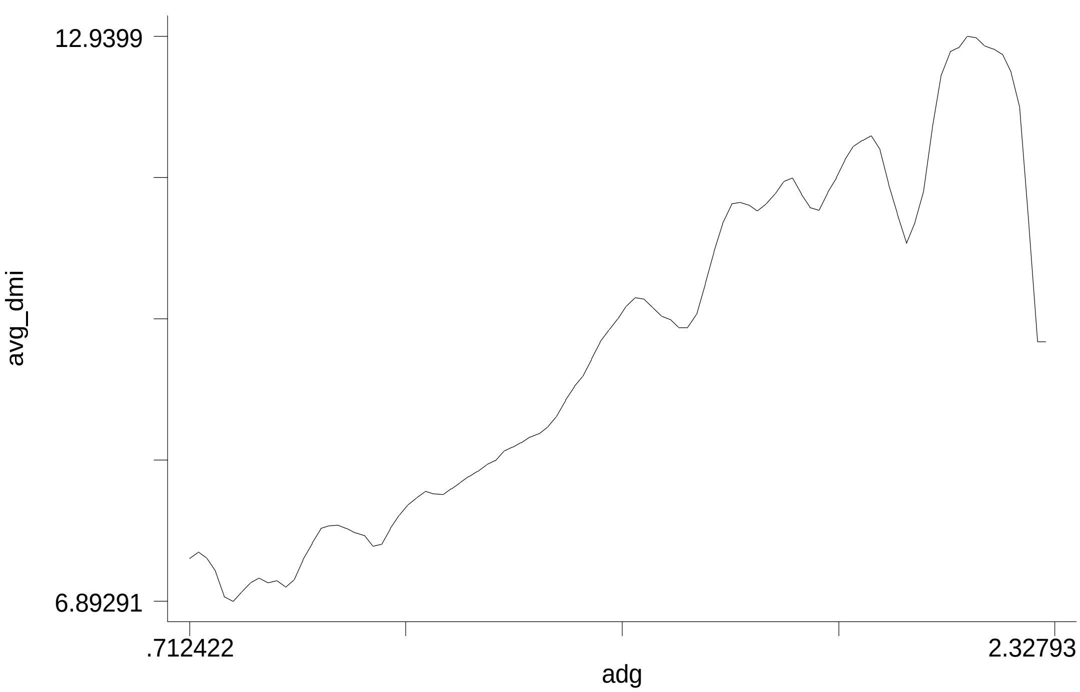

Figure 2 :Feed intake-average daily gain

Contemporary Group2

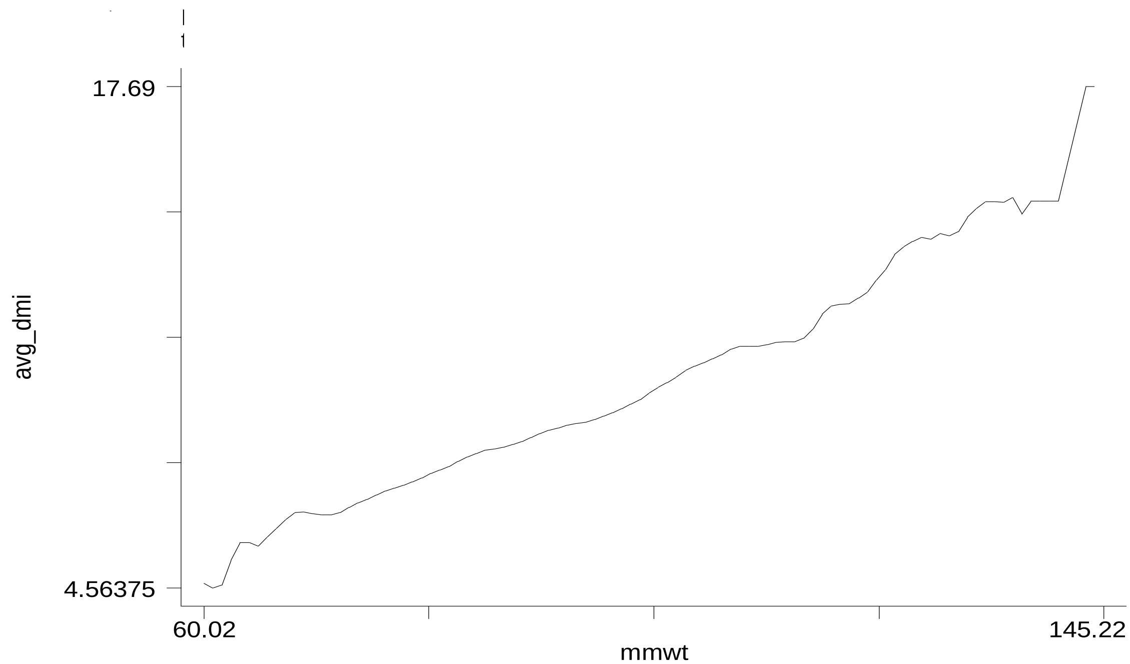

Figure 3: Average dry matter intake-mid metabolic body weight

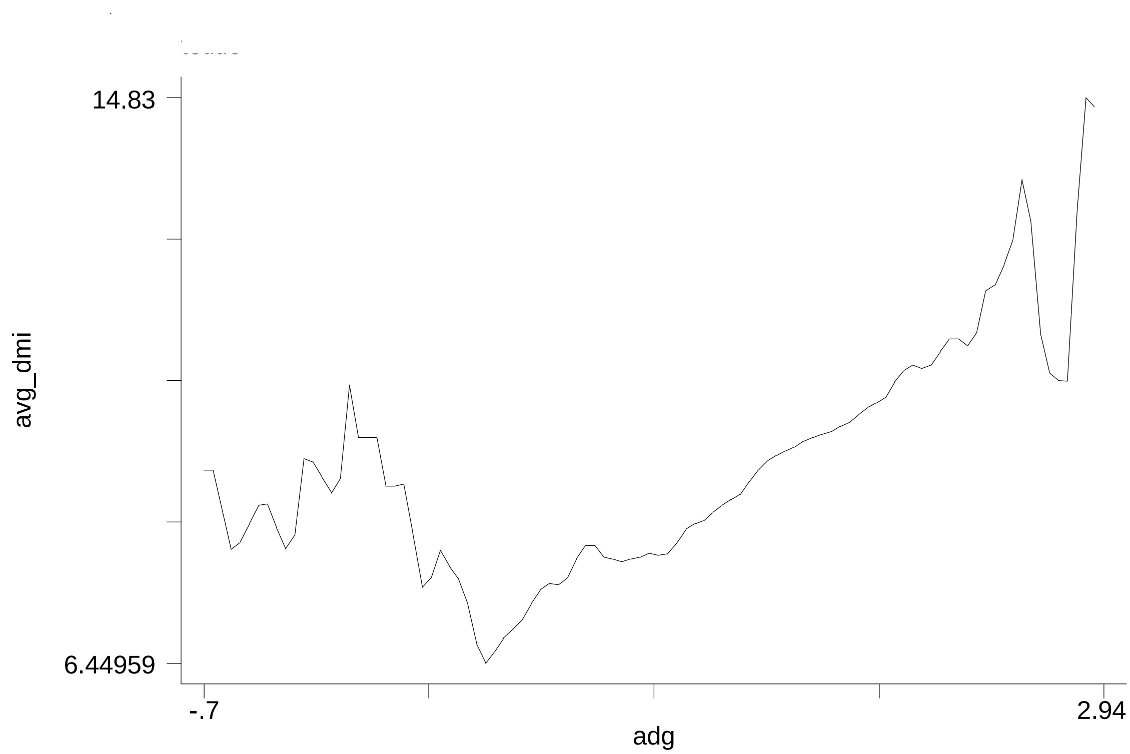

Figure 4: Feed intake-average daily gain

Contemporary Group 3

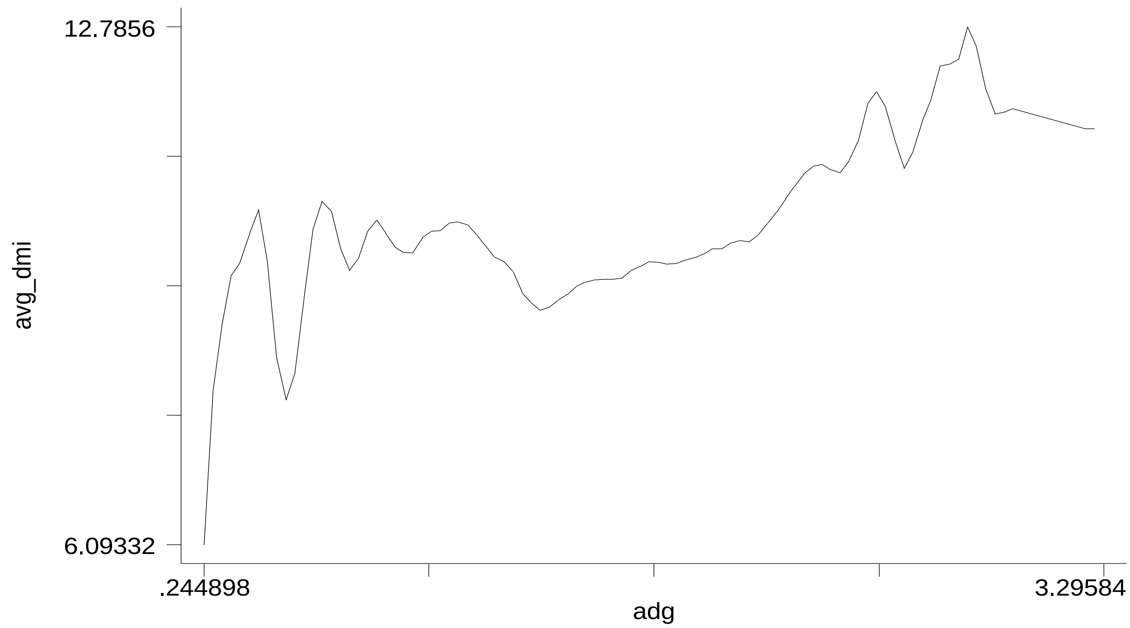

Figure 5: Feed intake-average daily gain

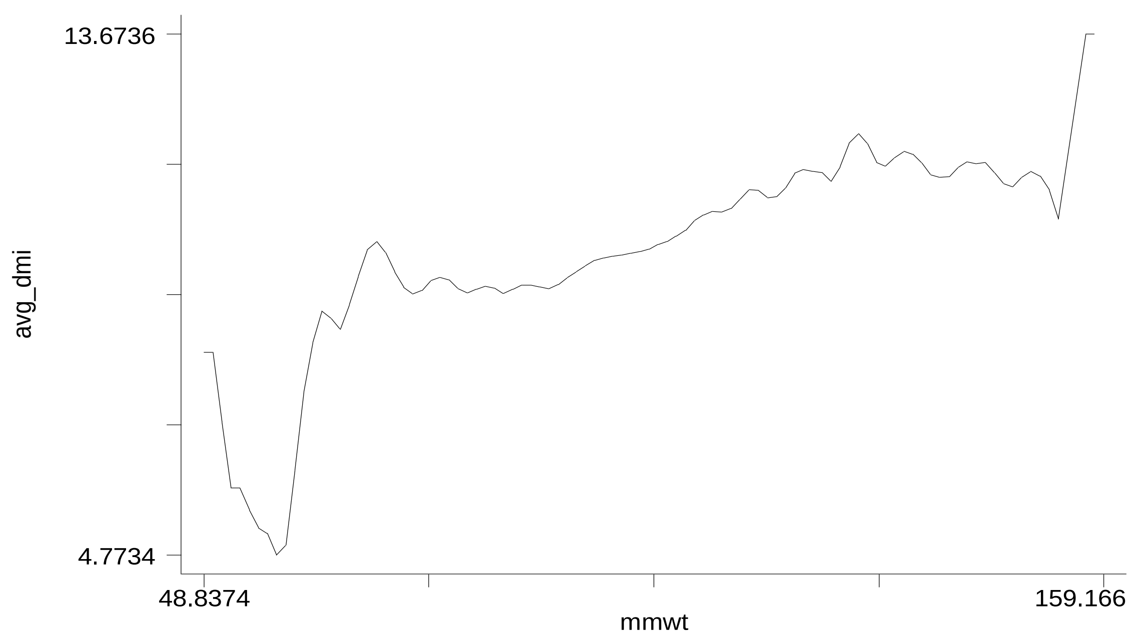

Figure 6: Feed intake and mid metabolic body weight

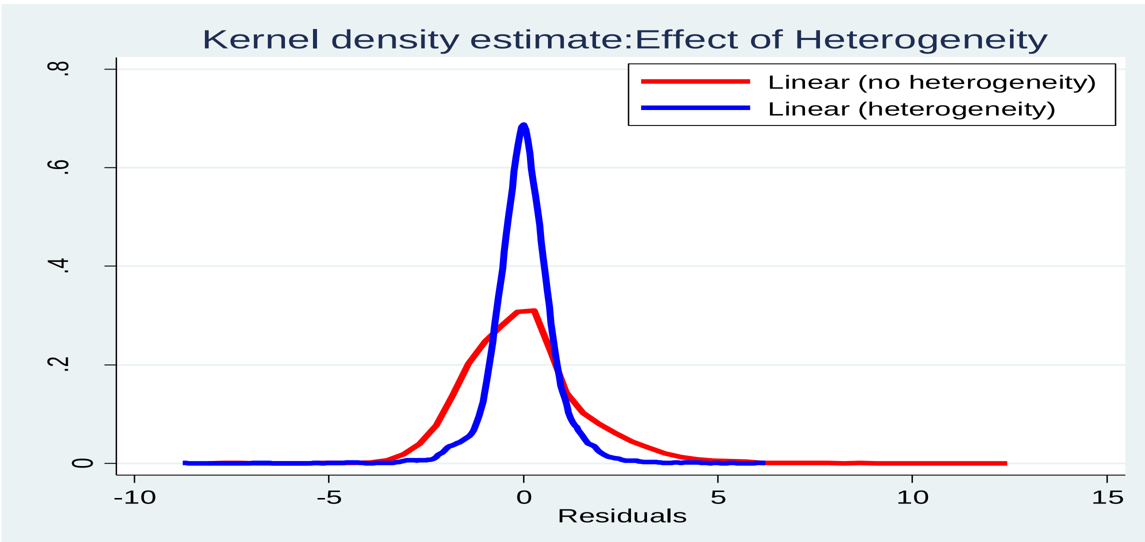

Figure 7: Kernel density estimates linear models

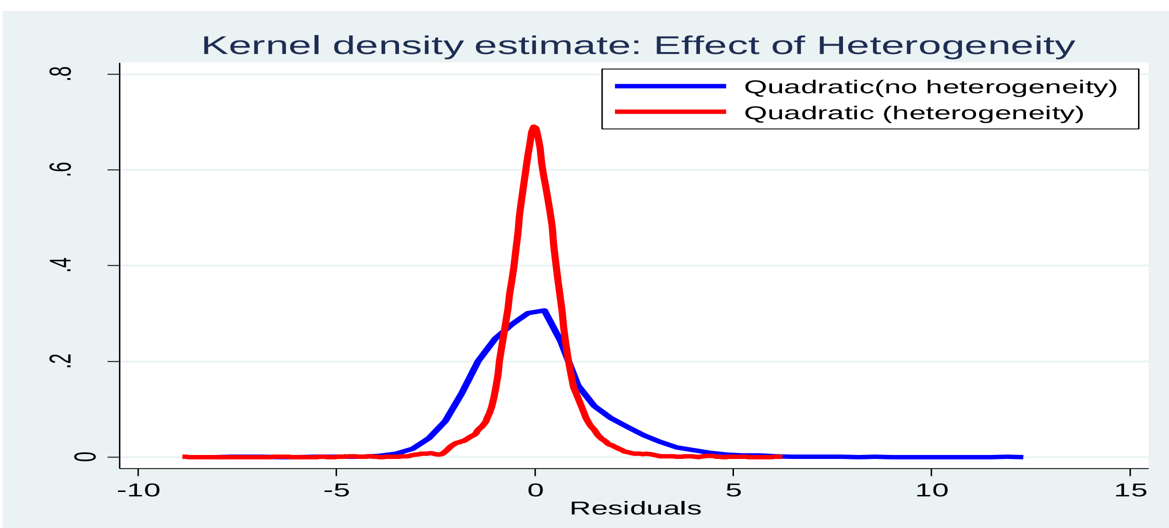

Figure 8: Kernel density estimates quadratic models

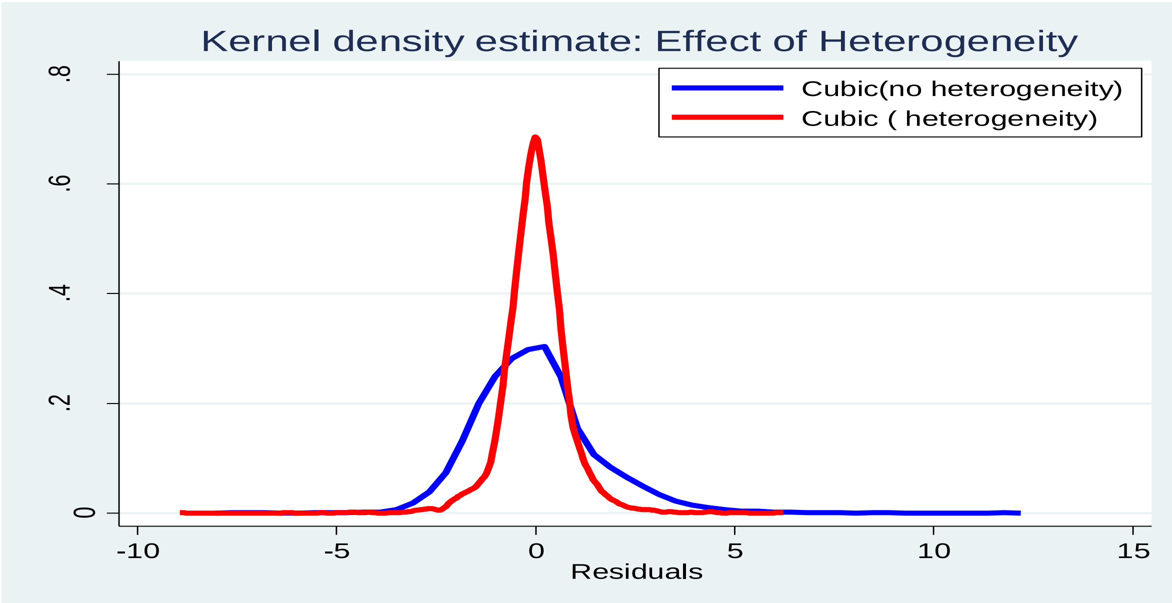

Figure 9: Kernel density estimates Cubic models

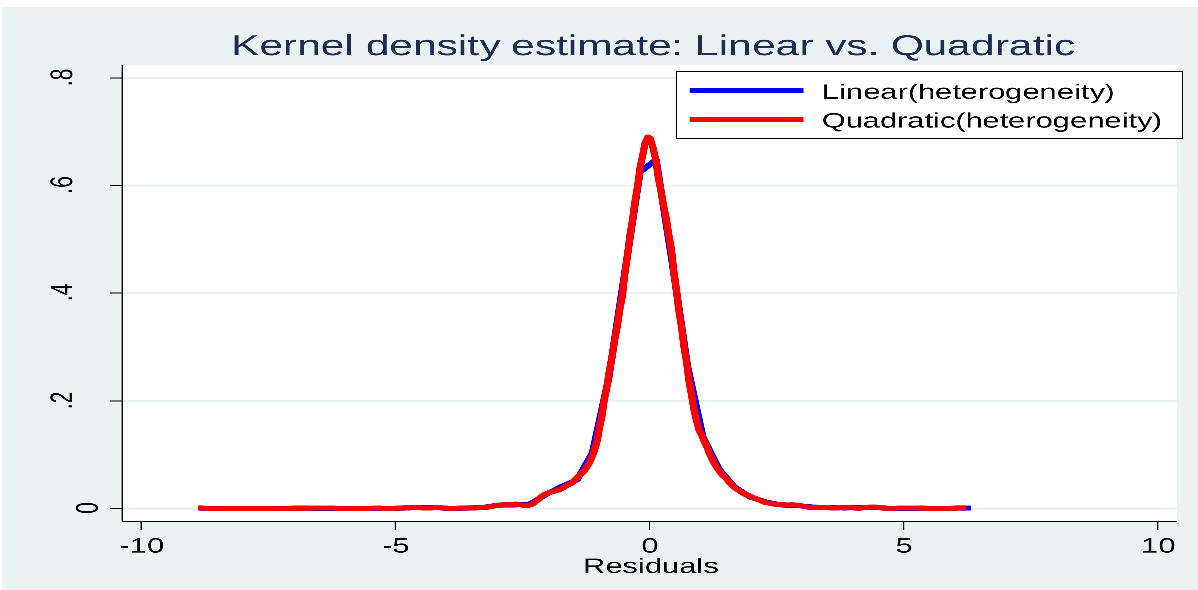

Figure 10: Kernel density estimates linear vs. quadratic

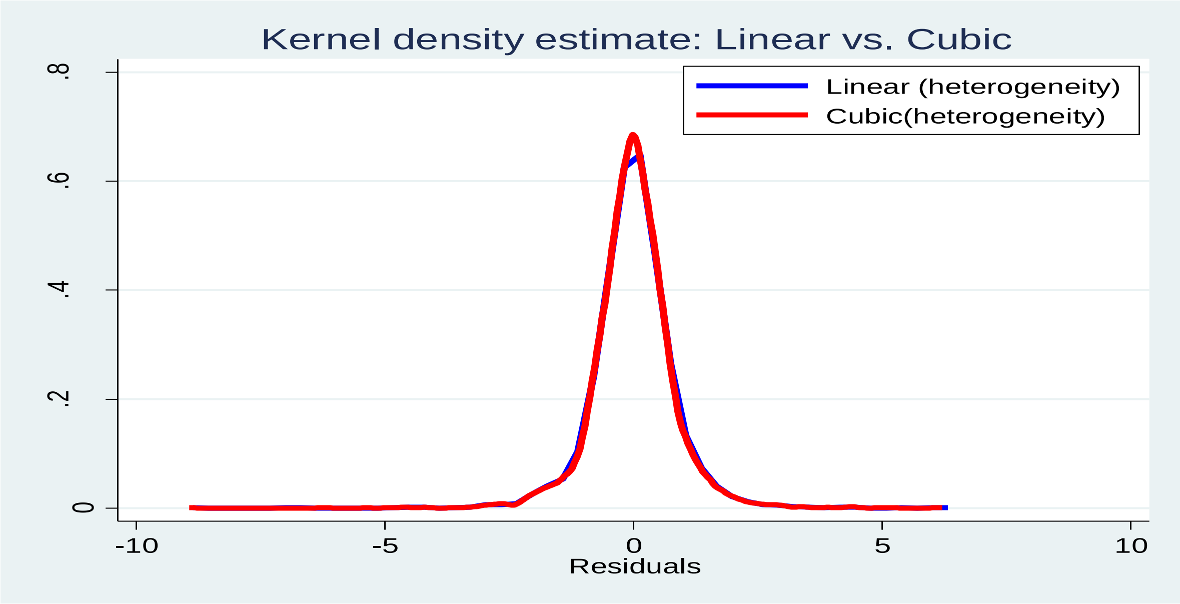

Figure 11: Kernel density estimates linear vs. quadratic