COW-CALF PRODUCER RISK PREFERENCE IMPACTS ON WILLINGNESS TO PAY FOR SUSTAINABLE BREEDING PRACTICES

BY

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Abstract

The role producer risk preferences on WTP is for sustainable breeding practices addressed in this paper using stated preference methods. Estimates of WTP amongst beef producers are compared with those the diary sector. Whilst preliminary indicate a relatively lower impact, these effects seem nuanced in dairy relative to beef. This suggests that influence of risk in the producer valuation of new technologies may be commingled with market structure effects.

Keywords: risk, beef cattle; dairy cattle; willingness to pay.

With global population projected to reach 9.6 billion by 2050 (UNPF 2011), producer adoption of sustainable breeding practices may be critical in meeting anticipated demand for high value foods. The livestock sector accounts for 7.1billion tonnes CO_2 equivalent (18%) of global greenhouse gas emission (FAO 2014). A major aspect of livestock GHG emissions is directly related to feed digestion process (enteric fermentation) in ruminants such as beef cattle. Methane emissions from enteric fermentation constitutes approximately 80% of agricultural CH_4 and 35% of anthropogenic methane emission[1] (FAO 2014). Reducing enteric fermentation is thus critical in enhancing the environmental sustainability of livestock production systems.

In this regard, a trait of particular significance is feed efficiency. Improved feed efficiency in beef is associated with lower dry matter intake, improved feed conversion and concomitant reductions in enteric methane emission (Alford *et al*. 2006; Basarab *et al*. 2013). As a greenhouse emissions abatement approach, breeding efficient cattle can result in the attainment (GHG) emissions reduction goals without compromising herd size or level of production. The use of more precise breeding technologies such as genomics therefore holds significant potential for sustainable beef production.

Genomic selection (GS) entails the use of whole genome molecular markers in estimating the genetic merit of a given animal. By simultaneously accounting for all DNA markers, GS incorporates more extensive genetic molecular information than marker assisted selection. Compared to conventional breeding, the advantages of genomic selection include the potential for increases in the rate of genetic gain and precision, and the extension of breeding goals to encompass traits typically difficult or costly to measure such as feed intake (Gaspa *et al.* 2012).

Producer valuation of different productivity, performance and carcass traits are well known (e.g. Walburger 2002; Chvosta *et al.* 2001; Roessler *et al.* 2008; Vestal *et al.* 2013); although little is known about feed efficiency. Specific to genetic technologies, empirical evidence suggests lower willingness to pay (WTP). Whilst conceding that cow-calf producers are typically slow adopters of technology, Vestal *et al.* (2013) identified that lack of confidence in the validity of genetic information as a potential contributory factor. It is conceivable given the uncertainties inherent in breeding, that producer risk preferences may be an important determinant of producer evaluation of the incorporation of genetic information in breeding. This notwithstanding, the role of producer risk preferences in beef cattle breeder WTP for genetic improvements has been largely unexplored. Pope *et al.* (2011) examined the impact cow-calf producer risk preferences on retained management and found evidence of a positive relationship between the degree of risk tolerance and calf retention. In this study, the impact of cow-calf producer risk preference on WTP for genomic improvements in feed efficiency is addressed. Further, a comparative assessment of risk preferences of dairy and cow-calf producer is undertaken in this study.

As a general attitude, risk preferences are rarely observable. With the increasing popularity of stated preference approaches however, these preferences may be elicited and categorised using risk-attitude measurement instruments (RAMI) (Fausti and Gillespie 2006). Using a contingent evaluation (CV) approach different technology preferences are evaluated amongst a sample of

[1] Totalling 2.2 billion tonnes of CO_2 equivalent.

cow-calf producers in Canada with varying underlying risk preferences. Farm and other producer characteristics are also elicited from the producer survey. Composite and disaggregated risk aversion measures are developed from producer responses to questions on different aspects of risk. A priori, the effect of risk preferences on technology selection is indeterminate. As an innovation in breeding, genomic improvements can have two identifiable but opposing effects. On the one hand, traits and breeding mechanisms are uncertain in terms of heritability and precision, suggesting risk averse producers may be less likely to express higher willingness to pay. A feed efficient herd on the other hand, may constitute a risk reduction strategy, attenuating the effects of input price risk. Considering the importance of feed costs on the economics of cattle production, this effect may be significant. Implicitly, the trade-off between perceived inherent risks of the breeding technology and its production risk reducing capabilities may be key in determining WTP for the technology.

This paper represents a unique contribution to the literature in a number of different respects. First, little has been done in eliciting the impact of risk on cow-calf producer preferences for input traits such as feeding efficiency using stated preference methods. Second, the use of genomic selection for improvement in feed efficiency in beef production systems is somewhat novel. By assessing producer WTP for genomically improved parent stock, this paper contributes to the literature on agricultural producer preferences for new technologies with potential impacts on environmental sustainability.

The rest of this paper is organized as follows: an overview of genomic selection is presented in section 2.0. The analytical section is captured in section 3.0. Results and conclusions are presented in sections 4.0 and 5.0 respectively.

2.0 Overview of genomic selection

Selection entails the identification of animals with superior genetic merit for breeding. This process has undergone continuous refinement in response to technical innovations and improvements. From phenotypic evaluations, to the inclusion of pedigree information to more recent molecular marker assisted methods, there has been shift towards increased precision in selection. As molecular marker assisted tool, genomic selection differs from conventional marker assisted selection (MAS) by simultaneously accounting for the effect of all markers (Single Nucleotide Polymorphism's) instead of a few (Jonas and de Koning 2013). Despite the large number of SNPs, the advent of DNA chip technology with high throughput has resulted in attainment of the cost effective genotyping of animals for the relevant markers (Meuwissen *et al.* 2001).

In genomic selection, genome wide genetic markers are used to identify individuals for breeding Meuwissen, *et al.* (2001). Habier *et al*. (2007) noted that genomic selection can be described as a two-step process: firstly, marker effects are estimated using genotypic and phenotypic data collected from animals in a training reference set. Secondly, genomic breeding values for any animal in the population can be predicted from the estimated marker effects.
Compared to conventional selection, genomic breeding has a number of advantages; In conventional cattle breeding, a breeder selects a bull (breeding sire) based on his expected breeding value (EBV) estimated from phenotype and pedigree information (Jonas and de Koning 2013). Aside from the high cost of progeny or relative testing, certain traits are not expressed until latter

stages resulting in relatively long generation intervals. With genomics, producers can circumvent the time lag synonymous with proving bulls as genomics breeding values (GEBVs) for young bulls can be predicted. Additionally, genomic applications in beef cattle breeding can result in increased accuracy of EBVs, and the enhanced efficiency in the utilization of genetic resources (Daetwyler *et al.* 2013).

The impact of genomics may be varied for different beef cattle traits. For traits such as feed efficiency, the potential impact is enormous. Despite the importance of feed cost in the overall farm production cost(i.e. estimated 70 per cent of total variable cost of production), feed efficiency has historically not been the focus of breeders as evident from the lack of published expected progeny differences (EPDs) for the trait by major breed associations(Anderson *et al.* 2005). This partly a result of the prohibitively expensive cost involved in the collection of phenotypic data on the trait. Consequently, a major appeal for genome association studies for feed efficiency remains the opportunity to leverage data more efficiently with minimal phenotyping (Rolf *et al.* 2011). Further, higher efficiency has been inexorably linked with reduced methane emissions indicating additional implications for the sustainable production systems.

2.1 Risk and producer decision making

Anecdotal evidence suggests that for any given producer the decision to adopt hinges critically on the difference between expected additional profits and the additional cost of adoption. Although WTP and adoption are distinct concepts, it is plausible that producers with higher WTP may be more likely to adopt. Indeed, Hudson and Hite (2003) examined producer WTP for precision application technology under the premise that WTP is positively correlated with the rate of adoption. Technology adoption has been identified as means to meet growing demand in both crop and animal production. Resultantly, technology adoption has been extensively examined (e.g. Gillespie and Davis 2004; Abdulai and Huffman 2005; Foltz and Chang 2002).

With respect to technology, the role of risk remains particularly relevant. Risk in producer decision making is multifaceted, encompassing perceptions and preferences, and production risk (Elliot *et al*. 2013; Popp *et al.* 1999).The former two are attitudinal whilst the latter is considered objective. These three interrelated identifiable aspects of risk have been evaluated in cow-calf production practices relative to the adoption of technologies and other value addition practices.

Elliot *et al.* (2013) examined the determinants of beef reproductive technology adoption amongst a sample of cow-calf producers in Missouri. Key determinants of the adoption of artificial insemination and estrus synchronization included operation type, producer risk and management practices .Popp *et al*. (1999) evaluated factors impacting cow-calf producer decision to retain weaned calves as value-added enterprise Perceptions about price risk significantly influenced calf retention decisions. Producers with lower perceptions of price risk were found to be more likely market calves at heavier weights.

Specific to decisions with potential implications on the environment, Kim *et al.* (2005) examined the determinants of adoption of best management practices (BMPs) by a sample of cow-calf producers. Risk preferences were elicited using the so called risk attitude measurement instruments (RAMI) (Fausti and Gillespie 2006). Specifically producers were asked to compare their likelihood of making investment decision as compared to their peers. In general, risk was negatively related to the adoption of capital intensive BMPs with uncertain outcomes. Suggesting producers placed less emphasis on the risk reducing potential of these BMPs. A major weakness of the approach

Kim *et al.* (2005) study was the use of a single construct to measure risk preferences. Penning and Gracia (2001) opined that multi-item approaches tend to be more effective in the extraction of producer risk preference given its multi-dimensional nature.

Other studies (e.g. Pope *et al.* 2011; Popp *et al.* 1999) elicited risk preferences using these multi-item approaches. Pope *et al.* (2011) evaluated the impact of cow-calf producer risk preferences on retained ownership. Producer risk preferences were defined as scores from the weighted combination of producer responses to a set of risk related questions. Risk averse producers were found to be more likely to market calves at weaning, implying a lower tendency to engage in value add practices.

In this paper an approach similar to Pope *et al.* (2011) is used to elicit cow-calf producer risk preferences. Unlike Pope *et al.* (2011) however, this paper is centered on WTP for genomic improvements. Further both composite and disaggregated measures of risk aversion are accounted for in this paper.

3.0 Analytical framework

Following Lusk and Hudson (2004) and Hudson and Hite (2003) the producers restricted profit function is specified as:

$\pi(p,z)$ where; $(p_1, p_2, ..., p_n)$ is vector of prices and z is a breeding technology for optimizing feed efficiency. Assume the initial z, z_0 is the conventional breeding technology. The introduction of new breeding technology in this case genomics denoted as z_1 results in new profit, specified as $\pi(p, z_1)$. The cow-calf producer's maximum WTP also defined shadow price (s) of the change in breeding technology is equivalent to: $s = \pi(p, z_1) - \pi(p, z_0)$.

3.1 Empirical approach

A double bounded contingent valuation method (Hanemann 1985) is implemented in this study. Each cow-calf producer is presented with two bids representing the cost of genotyping a bull for feed efficiency. The level of the second is contingent on a given producer's response to the first. If the producer is WTP an initial bid (T_M), a higher bid (T_H) is presented. The producer is presented with a lower bid (T_L) otherwise. This results in four possible outcomes: $\pi^{yy}, \pi^{nn}, \pi^{yn}, \pi^{ny}$, where the subscripts denote yes (y) and no respectively. Using Hanemann *et al.* (1991)'s notation, the respective likelihood functions for the utility maximizing producer for each of the different outcomes are:

$$\pi^{yy}\left(T_i^M, T_i^H\right) = \Pr\left\{T_i^H \leq \max\ WTP\right\} = 1 - G(T_i^H;\theta) \quad (1)$$

$$\pi^{nn}\left(T_i^M, T_i^L\right) = \Pr\left\{T_i^M > \max\ WTP \text{ and } T_i^L > \max\ WTP\right\} = G(T_i^L;\theta) \quad (2)$$

$$\pi^{yn}\left(T_i^M, T_i^H\right) = \Pr\left\{T_i^M \leq \max\ WTP \leq T_i^H\right\} = G(T_i^H;\theta) - G(T_i^M;\theta) \quad (3)$$

$$\pi^{ny}(T_i^M, T_i^L) = \Pr\left\{T_i^M \geq \max\ WTP \geq T_i^L\right\} = G(\mathrm{T}_i^M;\theta) - G(T_i^L;\theta) \quad (4)$$

Where θ is a parameter vector and is defined $G(T_i^k;\theta) = G(\alpha - \rho T_i^k + \lambda' z_i + \varepsilon_i)$ for $i = 1, ..., n$. The bid function takes the form:

$Y_i = \alpha - \rho T_i^k + \lambda' z_i + \varepsilon_i$, where α, ρ *and* λ are parameters, T_i^k is the initial bid presented to the producer and $\boldsymbol{z_i}$ is a vector of explanatory variables defined to include production and producer characteristics, and management traits. The corresponding likelihood function becomes:

$$\ln L(\theta) = \sum_{i=1}^{N} \begin{Bmatrix} d_i^{yy} \ln \pi^{yy}(T_i^M, T_i^H) + d_i^{nn} \ln \pi^{nn}(T_i^M, T_i^L) \\ + d_i^{yn} \ln \pi^{yn}(T_i^M, T_i^H) + d_i^{ny} \ln \pi^{ny}(T_i^M, T_i^L) \end{Bmatrix} \quad (5)$$

Where d_i^{kj}'s are indicator variables for *i*th producer. The maximum likelihood estimator of θ, θ is the solution to the differential of equation 5 i.e. $\frac{\delta \ln L(\theta)}{\delta \theta} = 0$ (Hanemann 1991).

3.1.2 Measuring risk

In the empirical literature different measures both implicit and explicit approaches have been implemented in the modelling risk. Regarding the latter, it is not uncommon to deduce the influence of risk in producer decision making through proxy variables such as age and other management practices. For example, younger producers tend to be innovative and more prone to taking risk as compared to older producers, thus commingling the effect of risk preferences and age (Fernandez-Cornejo 2007; Ward et al. 2008*)*. Elliot *et al.* (2013) used the number of replacement heifers retained on the farm as a proxy for production risk. Opinion variables regard perceived uncertainty of key market variables have also be used (Popp *et al.* 1999; Young and Shumway 1991).

In this study, a survey instrument was designed to elicit different aspects of risk; risk experience and knowledge, guaranteed vrs probable gambles, risk experience and knowledge etc., in order to incorporate all facets of risk. Questions were situated in a context congruous with producers' decision making. Composite and disaggregated measures of risk were developed from the responses elicited from the survey.

Data

The survey for the dairy sector was conducted in the summer 2013.Questionnaires were sent to 2520 producers randomly selected from dairy farmers across Ontario. Two hundred and five completed surveys were returned totalling a response rate of 8%. For the present analysis a subsection of the overall dataset was analyzed. Table 1.0 is a summary of the data.

Table 1: Descriptive Statistics

Variable	Mean	Std Deviation	Minimum	Maximum	Observations
Choice	.33	.47	0.0	1.0	1458
Price($)	43.48	33.51	0.0	85.0	1458
Genomic Info.	.331276	.47	0.0	1.0	1458
Daughters	35.63	42.17	0.0	100	1458
Milk	8024.69	5827.01	0.0	14000	1458
Somatic Cell Cnt	264.67	198.75	0.0	500	1458
AI	0.86	0.86	0.0	1.0	1458
Risk	3.97	1.36	0.0	9.0	1458
Income (%)	88.37	17.02	30	100	1458
Gender	0.95	0.95	0	1	1458
Education	12.32	4.34	0	18.0	1458
Age(Years)	46.41	13.08	19	65	1458
					1458

The main attributes evaluated include price, genomic information, number of daughters, milk production, somatic cell count. Other variables include the use of artificial insemination (AI), income(inc), gender, education(educ), age and risk. Genomic information (Geno), use of AI and gender were denoted as dummy variables.

4.0 Results

Table 2: Estimates of Conditional Logit (Marginal Effects)

Variable	Marginal Effect
Price	-***
Geno	+***
Daughter	+***
Milk	+***
Scount	-***

- negative significance at 1%, + positive significance at 1%.

Consistent with a prior expectation, price had a negative marginal effect whilst the genomic information, number of daughters and milk had positive marginal effects.

Table 3: Willingness to pay(WTP) estimates

Attribute	coefficient	WTP
Geno	0.54319	$18.75
Daughter	0.109	$3.76
Milk	0.0026	$0.10
Scount	-0.00815	-$0.28

Effect of Risk

Firstly the data set is segregated into two subsamples based on producer risks preferences. Producers with risk preferences greater than the mean are categorised as the high risk (HRISK) group (denoted as 1) whilst those with preferences lower than the mean are captured as low risk (represented by 0). This is interacted with all the attribute in order to ascertain the effect of heterogeneity due to differences in risk preferences (TABLE YYYY). The other demographic variables were also included in this model. Additionally, a separate model is estimated in which the aggregated risk(RISK) preference variable is interacted with the relevant attributes (TABLE XXX).

Table 4: Estimates of Conditional Logit (Marginal Effects): HRISK and Demographics

Variable	Marginal Effect
Price	-***
Geno	+
Daughter	+
Milk	+***
Scount	-***
HRISK*GENO	+
HRISK*DAUGHTER	-**
HRISK*MILK	+
HRISK*SCOUNT	-
AGE*GENO	-
AGE*DAUGHTER	-
AGE*MILK	+
INCOME*GENO	-
INCOME*DAUGHTER	+
INCOME*MILK	-*
INCOME*SCOUNT	+*
GENDER*GENO	-
GENDER*DAUGHTER	+
GENDER*MILK	-
GENDER*SCOUNT	+
EDUC*GENO	+*
EDUC*DAUGHTER	+
EDUC*MILK	-
EDUC*SCOUNT	+
AI*GENO	-
AI*DAUGHTER	-
AI*MILK	-
AI*SCOUNT	+**

*** 1%;**5%;*10%.

Table 5 :WTP ESTIMATES

Variable	WTP
Geno	$0.00
Daughter	$0.00
Milk	$0.02
Scount	-$0.95
HRISK*GENO	$0.00
HRISK*DAUGHTER	-$0.26
HRISK*MILK	$0.00
HRISK*SCOUNT	$0.00
AGE*GENO	$0.00
AGE*DAUGHTER	$0.00
AGE*MILK	$0.00
INCOME*GENO	$0.00
INCOME*DAUGHTER	$0.00
INCOME*MILK	$0.00
INCOME*SCOUNT	$0.00
GENDER*GENO	$0.00
GENDER*DAUGHTER	$0.00
GENDER*MILK	$0.00
GENDER*SCOUNT	$0.00
EDUC*GENO	$2.65
EDUC*DAUGHTER	$0.00
EDUC*MILK	$0.00
EDUC*SCOUNT	$0.00
AI*GENO	$0.00
AI*DAUGHTER	$0.00
AI*MILK	$0.00
AI*SCOUNT	$0.26

Table 6: Estimates of Conditional Logit (Marginal Effects): RISK and Demographics

Variable	Marginal Effect
Price	-***
Geno	+
Daughter	+
Milk	+*
Scount	-***
RISK*GENO	+
RISK*DAUGHTER	-*
RISK*MILK	+
RISK*SCOUNT	-
AGE*GENO	-
AGE*DAUGHTER	-
AGE*MILK	+
INCOME*GENO	-
INCOME*DAUGHTER	+
INCOME*MILK	-*
INCOME*SCOUNT	+**
GENDER*GENO	-
GENDER*DAUGHTER	+
GENDER*MILK	-
GENDER*SCOUNT	-
EDUC*GENO	+*
EDUC*DAUGHTER	+
EDUC*MILK	-
EDUC*SCOUNT	+
AI*GENO	-
AI*DAUGHTER	-
AI*MILK	-
AI*SCOUNT	+**

*** 1%;**5%;*10%.

Table 7: WTP Estimates

Variable	WTP
Geno	$0.00
Daughter	$0.00
Milk	$0.02
Scount	$0.88
RISK*GENO	$0.00
RISK*DAUGHTER	-$0.10
RISK*MILK	$0.00
RISK*SCOUNT	$0.00
AGE*GENO	$0.00
AGE*DAUGHTER	$0.00
AGE*MILK	$0.00
INCOME*GENO	$0.00
INCOME*DAUGHTER	$0.00
INCOME*MILK	$0.00
INCOME*SCOUNT	$0.00
GENDER*GENO	$0.00
GENDER*DAUGHTER	$0.00
GENDER*MILK	$0.00
GENDER*SCOUNT	$0.00
EDUC*GENO	$2.55
EDUC*DAUGHTER	$0.00
EDUC*MILK	$0.00
EDUC*SCOUNT	$0.00
AI*GENO	$0.00
AI*DAUGHTER	$0.00
AI*MILK	$0.00
AI*SCOUNT	$0.28

5.0 Conclusions

From the estimates of the conditional logit models, risk preferences of dairy producers have a negligible effect on WTP for genomic technologies. Potential factors may account for the low effect of risk preferences. Prominent amongst these is the market structure dairy production i.e. supply management in Canada. Extension of this study will be the inclusion of estimates of the beef survey, use other empirical approaches such random parameter models etc.

References

Abdulai, A., & Huffman, W. E. (2005). The diffusion of new agricultural technologies: The case of crossbred-cow technology in Tanzania. American Journal of Agricultural Economics, 87(3), 645-659.

Alford, A. R., Hegarty, R. S., Parnell, P. F., Cacho, O. J., Herd, R. M., & Griffith, G. R. (2006). The impact of breeding to reduce residual feed intake on enteric methane emissions from the Australian beef industry. Animal Production Science, 46(7), 813-820.

Anderson, R. V., Rasby, R. J., Klopfenstein, T. J., & Clark, R. T. (2005). An evaluation of production and economic efficiency of two beef systems from calving to slaughter. Journal of animal science, 83(3), 694-704.

Basarab, J. A., Beauchemin, K. A., Baron, V. S., Ominski, K. H., Guan, L. L., Miller, S. P., & Crowley, J. J. (2013). Reducing GHG emissions through genetic improvement for feed efficiency: effects on economically important traits and enteric methane production. Animal, 7(s2), 303-315.

Beauchemin KA, McAllister TA and McGinn SM 2009. Dietary mitigation of enteric methane from cattle. CAB Reviews: Perspectives in Agriculture, Veterinary Science, Nutrition and Natural Resources 4, No. 035.

Chvosta, J., Rucker, R. R., and Watts, M. J. (2001). Transaction costs and cattle marketing: the information content of seller-provided presale data at bull auctions. American Journal of Agricultural Economics, 83(2), 286-301.

Daetwyler, H. D., Calus, M. P., Pong-Wong, R., de los Campos, G., & Hickey, J. M. (2013). Genomic prediction in animals and plants: simulation of data, validation, reporting, and benchmarking. Genetics, 193(2), 347-36

Elliott, L., Parcell, J., Patterson, D., Smith, M. F., & Poock, S. (2013). Factors Influencing Beef Reproductive Technology Adoption. Journal of the ASFMRA.

Fausti, S., & Gillespie, J. (2006). Measuring risk attitude of agricultural producers using a mail survey: how consistent are the methods?. Australian Journal of Agricultural and Resource Economics, 50(2), 171-188.

Fernandez-Cornejo, J.(2007). Off-Farm Income, Technology Adoption, and Farm Economic Performance. Washington DC: U.S. Department of Agriculture, Economic Research Service, ERR-36.

Foltz, J. D., & Chang, H. H. (2002). The adoption and profitability of rbST on Connecticut dairy farms. American Journal of Agricultural Economics, 84(4), 1021-1032.

Food and Agriculture Organization (2014). The role of livestock in climate change. Livestock environment and development policy document [Available accessed: http://www.fao.org/agriculture/lead/themes0/climate/en/]. Accessed 12/03/014.

Gaspa, G., Pintus, M. A., Nicolazzi, E. L., Vicario, D., Valentini, A., Dimauro, C., & Macciotta, N. P. P. (2013). Use of principal component approach to predict direct genomic breeding values for beef traits in Italian Simmental cattle.Journal of animal science, 91(1), 29-37.

Gillespie, J. M., & Davis, C. G. (2004). Factors Influencing the Adoption of Breeding Technologies in US Hog. Journal of Agricultural and Applied Economics, 36, 35-4.

Grable, J., & Lytton, R. H. (1999). Financial risk tolerance revisited: The development of a risk assessment instrument. Financial services review, 8(3).

Jonas, E., and de Koning, D. J. (2013). Does genomic selection have a future in plant breeding?. Trends in biotechnology, 31(9), 497-504.

Habier, D., Fernando, R. L., & Dekkers, J. C. M. (2007). The impact of genetic relationship information on genome-assisted breeding values. Genetics, 177(4), 2389-2397.

Hanemann, W. M. (1985). Some issues in continuous and discrete response contingent valuation studies. Northeastern Journal of Agricultural Economics,14(1), 5-13.

Hanemann, M., Loomis, J., & Kanninen, B. (1991). Statistical efficiency of double-bounded dichotomous choice contingent valuation. American journal of agricultural economics, 73(4), 1255-1263.

Hudson, D., & Hite, D. (2003). Producer willingness to pay for precision application technology: Implications for government and the technology industry. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 51(1), 39-53.

Kim, S., Gillespie, J. M., & Paudel, K. P. (2005). The effect of socioeconomic factors on the adoption of best management practices in beef cattle production.Journal of Soil and Water Conservation, 60(3), 111-120.

Lusk, J. L., & Hudson, D. (2004). Willingness-to-pay estimates and their relevance to agribusiness decision making. Applied Economic Perspectives and Policy, 26(2), 152-169.

Meuwissen, T. H., B. J. Hayes, and M. E. Goddard. (2001). Prediction of total genetic value using genome-wide dense marker maps. Genetics 157:1819–1829

Pennings, J. M., & Garcia, P. (2001). Measuring producers' risk preferences: A global risk-attitude construct. American Journal of Agricultural Economics,83(4), 993-1009

Popp, M. P., Faminow, M. D., & Parsch, L. D. (1999). Factors affecting the adoption of value-added production on cow-calf farms. Journal of agricultural and applied economics, 31, 97-108.

Roessler, R., Drucker, A. G., Scarpa, R., Markemann, A., Lemke, U., Thuy, L. T., and Valle Zárate, A. (2008). Using choice experiments to assess smallholder farmers' preferences for pig breeding traits in different production systems in North–West Vietnam. Ecological Economics, 66(1), 184-192.

Rolf, M. M., Taylor, J. F., Schnabel, R. D., McKay, S. D., McClure, M. C., Northcutt, S. L., ... & Weaber, R. L. (2012). Genome-wide association analysis for feed efficiency in Angus cattle. Animal genetics, 43(4), 367-374.

Walburger, A. M. (2002). Estimating the implicit prices of beef cattle attributes: A case from Alberta. Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 50(2), 135-149.

Ward, C. E., Vestal, M. K., Doye, D. G., & Lalman, D. L. (2008). Factors affecting adoption of cow-calf production practices in Oklahoma. Journal of agricultural and applied economics, 40(3), 851-863.

Young, K. D., & Shumway, C. R. (1991). Cow-calf producers' perceived profit maximization objective: a logit analysis. Southern Journal of Agricultural Economics, 23(1), 129-136.

Vestal, M. K., Lusk, J. L., DeVuyst, E. A., and Kropp, J. R. (2013). The value of genetic information to livestock buyers: a combined revealed, stated preference approach. Agricultural Economics 44: 337-347.