Overview

Demonstrating the value of herd improvement in the Australian dairy industry

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Abstract. Herd improvement has been occurring since the domestication of livestock, although the tools and technologies that support it have changed dramatically. The Australian dairy industry tracks herd improvement through a range of approaches, including routine monitoring of genetic trends and farmer usage of the various tools and technologies. However, a less structured approach has been taken to valuing the realised and potential impacts of herd improvement. The present paper aims to demonstrate the value of herd improvement, while exploring considerations for undertaking such a valuation. Attractive value propositions differ among and within dairy stakeholder groups. While broad-scale valuations of genetic trends and industry progress are valued by government and industry, such valuations do not resonate with farmers. The cumulative nature of genetic gain and compounding factor of genetic lag means that long timeframes are needed to fully illustrate the value of genetic improvement. However, such propositions do not align with decision-making timeframes of most farming businesses. Value propositions that resonate with farmers and can lead to increased uptake and confidence in herd improvement tools include smaller scale cost–benefit analyses and on-farm case studies developed in consultation with industry, including farmers. Non-monetary assessments of value, such as risk and environmental footprint, are important to some audiences. When additionality, that is, the use of data on multiple occasions, makes quantifying the value of the data hard, qualitative assessments of value can be helpful. This is particularly true for herd recording data. Demonstrating the value of herd improvement to the dairy industry, or any livestock sector, requires a multi-faceted approach that extends beyond monetary worth. No single number can effectively capture the full value of herd improvement in a way that resonates with all farmers, let alone dairy stakeholders. Extending current monitoring of herd improvement to include regular illustrations of the value of the tools that underpin herd improvement is important for fostering uptake of new or improved tools as they are released to industry.

Keywords: animal breeding, EBVs, estimated breeding values, genetic gain, genetics, genomics, herd testing.

Introduction

Herd improvement has been occurring since the domestication of livestock species, with farmers seeking to improve subsequent generations of animals (Simm 2000). Since then, scientific knowledge and resources have advanced considerably (Weigel *et al*. 2017) and many new industry tools that support herd improvement have been delivered. For over 100 years, dairy herd improvement has been underpinned by milk recording (generally known as herd testing in the southern hemisphere). The milk sampling of lactating cows, which is normally performed monthly, is used for management decisions on farm and underpins genetic evaluation. The statistical approach of Henderson's (1953) best linear unbiased prediction method provided a way to disentangle

the influence of environment and genetics on an animal's performance. These estimates of the genetic merit of animals are known as estimated breeding values (EBVs). By providing a fair way of benchmarking and comparing animals across herds and countries, best linear unbiased prediction has had a major impact on the potential for herd improvement.

Today, DataGene (Melbourne, Victoria, Australia) publishes EBVs on 42 traits for Australian dairy farmers, including milk-production traits, fertility, longevity, health and efficiency traits. To simplify selection decisions, the information from EBVs is summarised into a single index value. EBVs are weighted by their respective index weights, generally derived from economic values and genetic

parameters using selection index theory, an approach proposed by Hazel (1943). The national dairy selection index in Australia is the Balanced Performance Index (BPI) that includes key traits contributing to profitability, each weighted by their respective economic value (Byrne *et al*. 2016).

Herd improvement in the Australian dairy industry is monitored through several approaches. The success of breeding programs can be measured by tracking genetic trends over time (Pryce *et al*. 2018*a*). The doubling of average genetic gain in the past decade from AU$10/year in sires born from 2005 to 2009 to AU$20/year (Fig. 1) is an important metric of herd improvement. However, there is large variation in the rate of genetic gain among herds. For example, using data from 581 Holstein herds (obtained from DataGene (Bundoora, Victoria, Australia) in November 2019) and applying a within-herd linear regression of BPI on year of birth between 2010 and 2014, the rate of genetic gain ranged between –AU$15/year to AU$35/year (99% confidence interval). The improvements in genetic gain that have been made can be largely attributed to genomics and extension. The implementation of genomic selection has reduced generation interval and increased EBV reliability. The National Breeding Objective Review in 2014 was an extensive consultative process with industry and farmers to support, develop and agree on the current indices used in the Australian dairy industry (Martin-Collado *et al*. 2015). The formation of DataGene has resulted in a more coordinated approach to herd improvement and increased investment by key stakeholders in the herd improvement space. This has facilitated broader awareness of validation studies such as Feeding the Genes and increased the uptake of some herd improvement tools such as the Good Bulls Guide, Genetic Progress Report and commercial genotyping of heifers and bulls.

However, similarly to variable rates of genetic progress among farms, variable uptake in herd improvement tools has also been observed. For example, although increasing numbers of bulls and commercial females are being genotyped (DataGene 2019*a*) and genomic semen usage is on the rise (NHIA 2020), approximately two-thirds of Australian dairy herds have less than 80% of their replacements sired by an artificial insemination sire (DataGene 2019*b*). 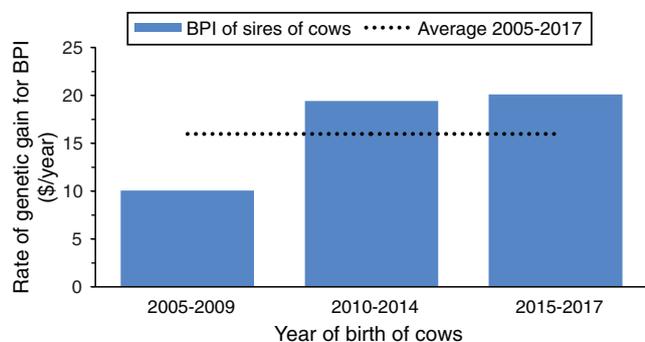This has an impact on genetic progress, as herd bulls are generally of lower genetic merit than are artificial insemination sires (Byrne *et al*. 2016). Also, without a recorded pedigree, these calves do not receive an EBV. There has also been declining participation in herd testing. Between 2005–2006 and 2016–2017, the number of cows tested reduced from 48% to 39% of the national herd (DataGene 2018). This drop is in part explained by declining farm and cow numbers, an increase in alternate on-farm measurement devices, such as in-line meters (Watson and Watson 2016), and financial pressures of the millennial drought, global financial crisis and milk price step-down. In addition, individual farmer usage and awareness of decision support tools is monitored through regular surveys by Dairy Australia. The 2016 survey (Watson and Watson 2016) showed that not all farmers were aware of the BPI 1 year after its release, and of those that are aware, not all use it for making selection decisions. Today, farmer awareness of the BPI has now reached 80% (Watson 2019).

Despite this large coordinated effort monitoring genetic trends and uptake and awareness of herd improvement tools, historically, a less structured approach has been taken to valuing the realised and potential impacts of uptake (or decline) of these tools in the dairy industry. Perhaps, it is, in part, because of the challenge of doing so. Herd improvement comprises many components, and, therefore, attributing a monetary worth is hard. Also, definitions of value extend beyond monetary worth to encompass the importance or usefulness of something (Cambridge University Press 2011). The present paper aims to demonstrate the value of herd improvement and explore the considerations for undertaking such a valuation, including; the target audience and how this influences value proposition, the scale and timeframe of valuation, non-monetary assessments of value and additionality in data usage.

Considering the target audience

When applying the definition of value to herd improvement, there are several considerations. First, the perceived usefulness, or importance of something, which is a measure of value (Cambridge University Press 2011), can be a subjective assessment. For instance, perceptions of the value of herd testing have been found to differ among farms, being influenced by both prior exposure and farm business stage (Newton *et al*. 2020). This means an attractive value proposition can differ among farms. Previously, Waters *et al*. (2009) also identified differing priorities among farmers and recommended multiple messages be used to address these different priorities. Second, the target audience for value propositions influence why there is a need to demonstrate value and what presentation of value will resonate with them. For example, large, broad-scale valuations at national or regional levels are valuable to government and industry for reporting on genetic trends and industry progress (e.g. Table 1 includes example key performance indicators for the Australian dairy industry). However, these key performance indicators do not necessarily provide an attractive value proposition at the farm level. Therefore, there is a need to consider multiple approaches to valuation, including non-monetary or qualitative assessments of value. To effectively engage farmers with herd improvement, it has previously been suggested that increasing alignment

Fig. 1. Average rate of genetic gain for sires of Holstein cows by year of birth over three time periods. Figure was adapted from DataGene (2018).

Table 1.　Example Australian dairy industry key performance indicators (KPI) used for herd improvement

Baseline, target and achieved metrics for each KPI are given where available. BPI, Balanced Performance Index; HWI, Health-Weighted Index; TWI, Type-Weighted Index; APR, Australian Profit Ranking, predecessor to the BPI; EBVs, estimated breeding values

Source	KPI	Baseline	Target/achieved
ImProving Herds Project	Proportion of farmers using Australian metrics as the criteria for bull selection[A]	2013: 44% of farmers say APR influences their selection decisions	2018: 65% of farmers using Australian metrics Achieved: 80% are aware of BPI, HWI or TWI 78% of farmers say EBVs influence selection decisions[C]
	Proportion of semen sold from young genomic bulls[B]	2013: 25% of semen sold comes from young genomic bulls	2018: 45% of semen sold comes from young genomic bulls Achieved: 47.4% of semen sold comes from young genomic bulls
Dairy Australia Evaluation Framework 2020–2025[D]	Accelerated genetic progress in feedbase and animal breeding	2020–2021: the rate of genetic gain of BPI of sires of cows is AU$24/year; the rate of genetic gain of cows in BPI units is AU$18/year	2024–25: the rate of genetic gain of BPI of sires of cows is now AU$30/year; the rate of genetic gain of cows in BPI units as a result of heifer genomic testing is AU$25/year
	Routine management decisions of dairy farm businesses (e.g. sire selection, irrigation scheduling, culling) are informed by multiple data sources	No baseline available	2024–2025: 80% of dairy farms are using multiple data sources in decision making
Herd Improvement Strategy 2019–2024[E]	Increase the measurement of individual cow performance through an increased number of cows participating in herd testing and increased data accessed from farms with in-line meters	2016: 20% of farms have in-line meters 2017: 39.6% of cows are herd tested	2024: data accessed from herd test participants and farms with in-line meters for measurement of individual cow performance represents over 60% of the national herd
	The majority of dairy farmers and service providers are making data-informed decisions to drive animal performance, improve profitability and meet value chain requirements	2016: 47% of farmers using Good Bulls Guide	2024: 75% of farmers are using the Good Bulls Guide or app as a source of sire data

[A]Sources: Watson and Watson (2013, 2016); Watson (2019). Some questions asked in 2016 and 2019 surveys were changed, so not all results are directly comparable.
[B]Source: NHIA (2020).
[C]Dairy Australia's Animal Husbandry and Genetics Survey is conducted only every 3 years, so values are from 2019.
[D]Dairy Australia (2020*b*).
[E]Herd Improvement Industry Strategic Steering Group (2019).

between farmer decision-making and usage of genetic tools requires a demonstration of how genetic improvement is making a difference in dollar terms on farm as part of a coordinated strategy and comprehensive development program (Nettle *et al.* 2010). In addition, the benefits of working with partner farms in Australian dairy research and extension are well described (Crawford *et al.* 2007), with farmers having a preference to learn from other farmers (Blair *et al.* 2013). A research, development and engagement strategy that demonstrates a multi-faceted value proposition at the farm level, engages partner farms in research, and provides a platform for farmers to learn from other farmers is more likely to deliver an attractive value proposition and drive practice change in farmer use of herd improvement tools.

Macro- and micro-valuations of herd improvement

Several different approaches have been used in macro-valuations of genetic improvement, that is, in very large datasets or at a national level. Here, we will first describe two examples applicable to the dairy industry, demonstrating links between performance and genetic merit and measures of income or profit and genetic merit. Then, we consider two approaches for demonstrating the value of herd improvement at the herd (micro) level, namely, the use of on-farm case studies and cost–benefit analyses.

Macro-valuation, Example 1: genetic gain versus phenotypic improvement

Illustrations of the link between genetic gain and phenotypic improvement are often used as illustrations of the value of

genetics. For example, using a large Australian dataset Morton (2011) indicated that cows with higher EBVs for fertility had higher 6-week in-calf rates. Similarly, an across-herd study of 505 dairy herds showed that cows sired by high Australian Profit-Ranking bulls, the precursor to the BPI, had greater milk yields than did those sired by lower ranked bulls, and were just as likely to last in the herd (Morton *et al*. 2015). They also found that while level of supplementary feeding influenced the magnitude of difference between cows, it did not affect direction of trends. Recently, Cole *et al*. (2020) illustrated the proportion of improvement in milk protein yield of US Holstein cattle attributable to improved genetic and environment (management). Using a similar approach on Australian data, one-third of the gain in protein yield since 1990 can be attributed to genetic improvement (Fig. 2). Similarly, 31% of the annual gain in Australian average milk yield per cow since 1980 is attributable to genetic improvement (Fig. 3). Although genetics has had a smaller effect than have management changes on milk production gains, genetic improvement is permanent and cumulative.

Macro-valuation, Example 2: genetic gain versus profit

Although many modern selection indices, including the BPI, are expressed as expected profit per cow per year (Byrne *et al*. 2016), few validation studies of the link between genetic merit and profit are apparent. By multiplying change in milk EBV since 1980 by the actual milk prices (ABARES 2019), adjusted for inflation (ABS 2020), our example from above (Fig. 3) can be extended. Genetic improvement in milk yield since 1980 contributed an additional milk income of AU\$493 per cow per lactation in 2018. Extrapolating this across the population of herd recorded cows, genetic improvement in milk yield since 1980 represented an additional AU\$176.8 million of milk income in 2018. As genetic gain is cumulative, summing the total value of genetic improvement made in milk yield

for herd recorded cows every year since 1980 exceeds AU \$4.87 billion. However, such valuations are limited, as they do not account for the costs of producing this extra milk. The study by Ramsbottom *et al*. (2012) is one of few studies to directly explore the link between genetic merit and profit in dairy cows. In a large study of Irish dairy herds, Ramsbottom *et al*. (2012) reported that a 1 unit increase in the Economic Breeding Index, Ireland's national index, was associated with an €1.94 (≈AU\$2.76) increase in the net margin per cow. Although Ramsbottom *et al*. (2012) adjusted for year, stocking rate, herd size and purchased feed, it is unlikely that such an approach enables that all variables that influence farm profit, especially management decisions, can be effectively accounted for.

More broadly, as modern selection indices consider many aspects of cow performance (Cole and VanRaden 2018; Pryce *et al*. 2018*a*), the cumulative value of genetics and herd improvement in the Australian dairy industry is much greater than the impact on milk income illustrated here. This value will continue to increase, most likely at faster rates than in the past, as genotyping of females becomes more common place and new data sources and analytical techniques support continued development of new and improved EBVs. Incorporation of routine, national approaches for quantifying the value of herd improvement would complement existing measurement of genetic gain and technology use.

Micro-valuation, Example 1: validating herd improvement through on-farm studies

To apply the recommendations of Nettle *et al*. (2010) and Crawford *et al*. (2007) to the development of a valuation of genetics that would resonate with farmers, we recruited diverse farms representative of the broader industry for use as on-farm case studies. Consequently, we engaged 27 farms representative of the diversity of Australian dairy industry
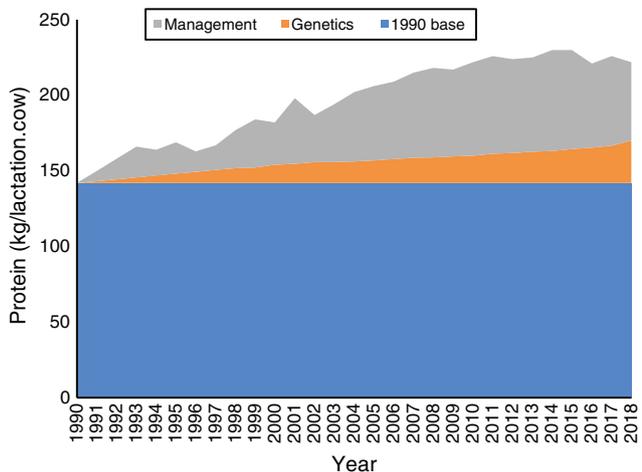

Fig. 2. Graph showing the increase in milk protein (kg) since 1990, partitioned out to show the proportion of increase in milk protein (in kg) since 1990 attributable to genetics (orange) and management (grey) relative to the average production in of 1990 (blue) in herd-recorded Holsteins and Jerseys. Source: DataGene Ltd (https://datagene.com.au/DataServicesDataServices, accessed November 2018).
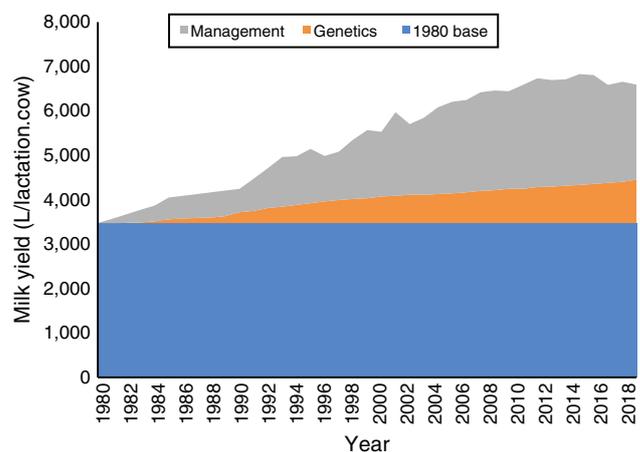

Fig. 3. Graph showing the increase in milk yield since 1980, partitioned out to show the proportion of increase in milk yield (in L/cow.lactation) attributable to genetics (orange) and management (grey) relative the average production in 1980 (blue) in herd-recorded Holsteins and Jerseys. Source: DataGene Ltd (https://datagene.com.au/DataServicesDataServices, accessed November 2018).
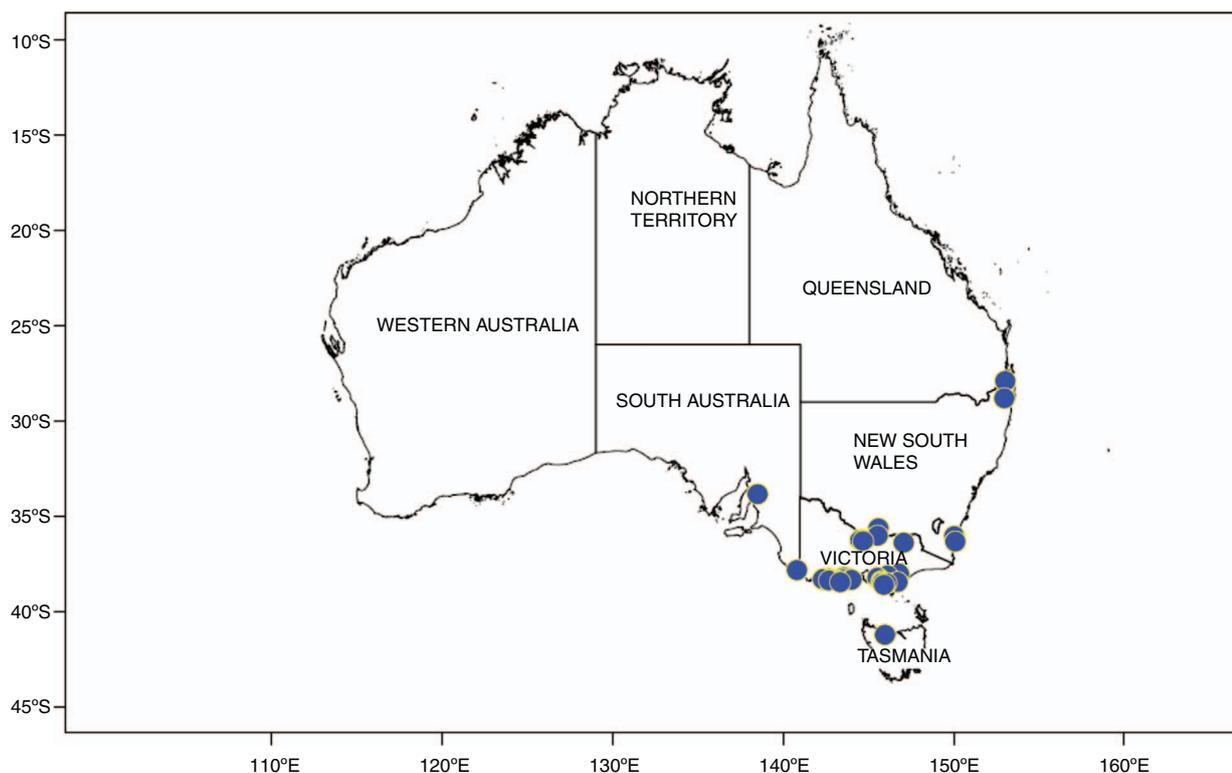
Fig. 4. Location of case-study farms whose data were used to demonstrate the value of genetics to farm businesses. A multi-disciplinary selection panel reviewed the 70 expressions of interest received considering region, feeding system, calving pattern, herd size, breed and interest level in genetics, so as to ensure focus farms reflected diversity of Australian dairy industry.

Table 2.   Average difference in Balanced Performance Index (BPI), productive life and annualised milk production parameters between the top 25% and bottom 25% of cows ranked on BPI within herd-years
Results are presented as the average within-herd difference observed in 29 herds (n (cows) = 13 371)

Parameter	BPI	Productive life (months)	Milk (L/cow.year)	Fat (kg/cow.year)	Protein (kg/cow.year)
Difference	172	8	649	50	38

(Fig. 4). Economic, performance and EBV data from these farms were used to develop a within-herd approach for demonstrating the value of genetics to farm businesses. This was first described in Newton *et al.* (2017*b*) and has since expanded as additional data have become available. The performance of the top and bottom 25% of cows (ranked on BPI) within each herd was compared. Because it was a within-herd analysis, cows were fairly compared with their herd mates, that is, they had similar management, environment and diet. Each cow's lifetime values were divided by their productive life (in days) and multiplied by 365 to produce yearly values for fair comparison. In every herd ($n = 29$), the top 25% of cows outperformed their low-BPI herd mates, on average, producing 88 kg more milk solids a year. These cows also lasted as long or longer in the herd, with the average productive life 8 months longer (Table 2).

Individual cow lifetime performance information was combined with farm financial data to calculate margin over feed and herd costs (MOFH) as a measure of contribution to farm profit in a subset of herds ($n = 5$). This measure was reached following iterative cycles of feedback and consultation with dairy farmers, economists, service providers and technical independent geneticists from overseas. Each cow's MOFH was calculated by summing income from milk, calf sales and final salvage value and subtracting costs of rearing, feed and those associated with mating and mastitis events. As described in Newton *et al.* (2017*b*), all financial measures were calculated as net present values, assuming a 5% discount rate, and then presented as an annual value. On average, high-BPI cows contributed ~AU $300 per cow per year more to MOFH than did their low-BPI herd mates. Additional milk income easily compensated for

higher feed costs of these cows, with a sensitivity analysis of current milk prices and feed costs showing this to be true even if milk price dropped by 50% and feed prices stayed the same or feed price doubled and milk prices stayed the same.

Farms are complex systems. Ho *et al*. (2013) illustrated that no one measure of farm performance was a good predictor of profit. Therefore, genetic merit is one of many factors influencing financial performance, and whether a high genetic merit herd is a profitable one will be influenced by many factors. However, demonstrating that cows of differing genetic merit make different contributions to farm margins illustrates that genetics is of value to farm businesses. How this knowledge is then implemented within a farm system is likely to be constrained by the individual parameters of that farm. For example, stocking rate may need to be adjusted as higher genetic merit cows with increasing feed demands enter the herd. Replacement heifer strategies may need to be adjusted as the herd improves its fertility and more high genetic merit heifer calves are born each year.

Micro-valuation, Example 2: cost–benefit analyses

Cost–benefit analyses are often used to estimate the value of adopting a herd improvement tool on-farm. A growing number of studies are presenting farm-level cost–benefit analyses of genotyping heifer replacements at varying levels of complexity. One approach is the use of complex (usually stochastic) simulations to model the impact of genotyping across all areas of the farm. For example, Hjortø *et al*. (2015) reported on the change in operational return, which encompasses all sale income minus variable costs of cows and young stock, when exploring adoption of genotyping. This modelling approach also facilitated the use of genomic information multiple times over the animal's lifetime. Bérodier *et al*. (2019) calculated overall net margin in a mechanistic, stochastic and dynamic model to compare genomics and usage of sexed dairy, conventional dairy and beef semen under three French dairy farming systems. They found that over a 10-year period, incorporating genotyping increased genetic gain in all scenarios compared with selecting on the basis of parent average EBVs. However, break-even genotyping prices were low and heavily influenced by farming system. They ranged from −€1.4 to €12.8 for a farm selling into the fresh milk market, −€5.2 to €27.8 for a farm selling into organic markets to €5.3 to €36.3 for a farm selling milk for cheese production. While such approaches can offer useful insights as they consider the flow-on effects of a change of one element of a farm business, findings can be highly specific to a particular dairy farming system and current prices. Results from such analyses may not be broadly applicable over time or in countries such as Australia where dairy businesses operate in diverse conditions.

Simple case studies that focus on the cost of genotyping and a benefit realised through the increased accuracy with which herd replacements are chosen may better support the development of value propositions as conclusions are less influenced by prevailing market conditions. For example, both Calus *et al*. (2015) and Weigel *et al*. (2012) focussed on the cost of genotyping and a benefit realised only through

the increased accuracy with which herd replacements are chosen. At a genomic test cost of US$40/head, Weigel *et al*. (2012) reported that net benefit from genotyping heifer calves ranged from US$28 to US$259, depending on the proportion of females retained, where the benefit is the average gain in EBVs of selected females. Alternatively, Calus *et al*. (2015) and Newton and Berry (2020) reported results as standard deviations of a breeding goal (selection index). This approach means that conclusions and summaries are easily transferrable as market conditions change or national breeding goals are revised. As the benefit from genotyping is also heavily affected by herd parameters such as replacement rate and reproductive performance, another strategy for supporting adoption is to develop simple decision-support tools (Newton and Berry 2020). Such tools, including the genomic value tool of DataGene (https://uat.datavat.com.au/heifer-selector, accessed 26 October 2020) enable customised value propositions to be derived for individual farm adoption of genomic testing.

Timeframe for valuation

Genetic lag and the cumulative nature of genetic gain both pose challenges in demonstrating the value of genetic and genomic tools, especially on farm. The average superiority of the next generation is a function of the proportion of individuals chosen (selection intensity), the accuracy of the information available and the variation in the population as described in the breeder's equation (Falconer 1989). Provided selection pressure exists (i.e. not all progeny are chosen to produce progeny of their own), genetic gain accumulates, and each subsequent generation of animals is superior to the one preceding it. As genetic gain is cumulative, a long-term approach to valuation, in principle, offers a more attractive value proposition for industry. For example, revisiting the impact of compounding on genetic improvement on milk yield (Fig. 3), since 1980 the milk EBV has increased an average of 27 units/year. After 10 years (in 1990), the milk EBV is 244 units higher than it was 1980, while in 2018, after 28 years of selection, the milk EBV is 979 units higher. For similar reasons, the break-even cost of genetic tools can be higher when longer timeframes are considered. For example, Boichard *et al*. (2013) found that the break-even cost of genotyping to choose herd replacements is higher when a longer timeframe is considered, €25 after 5 years and more than double that (€59) after 25 years. Genetic lag and cumulative genetic gain prevent full expression of benefits in short time periods; so, a higher breakeven cost means that more can be paid for the genotyping service. As costs of genomic testing have decreased, genotyping investments can be recouped in shorter timeframes.

The impact of genetic gain being cumulative is further compounded by the fact that most herd improvement investments do not show results in dairy businesses for several years due to genetic lag. This has particularly been a challenge under the structure of progeny-testing schemes, with genetic lag of 5–6 years (Pryce and Daetwyler 2012). Genomic

selection has dramatically increased rate of genetic gain in dairying (Weller *et al*. 2017); bulls are now selected and used at much younger ages on the basis of genomic EBVs. However, genetic lag is still a challenge as it is still nearly 3 years after a bull's semen is used before his daughters enter the milking herd. Similarly, while genomic EBVs enable early informed decisions about female replacements, there is also a lag of several years before they enter the milking herd. Also, most economically important traits, such as fertility, milk production and longevity, are not fully expressed for several years after entering the herd (Byrne *et al*. 2016). The tendency of industry-wide strategic planning to consider a longer-term outlook, for example, Australian Dairy Sustainability Framework 2030 goals (Dairy Australia 2020*a*) and National Farmers Federation 2030 strategy (NFF 2018), show that a long-term lens in calculating value or return on investment is accepted in research and industry.

When discussing value at a farm level, this is not the case, and shorter timeframes need to be considered. One of the characteristics of genetics identified as most off-putting by advisors was the period of time between making a choice and seeing the outcome (Axford *et al*. 2015). Comparing genetic investments over a 20-year period alongside investments in other business areas where value is seen almost immediately (i.e. supplementary feeding, fertiliser) is a challenge. In their simulation of the value of selecting replacement heifers using genomic breeding values, Calus *et al*. (2015) proposed that the cumulative effects of genetic gain via cow-to-cow pathway could be ignored as they had previously been shown by Van Tassell and Van Vleck (1991) to be small compared with those of other dairy selection pathways. Ignoring cumulative genetic gain means that a discrete generation of animals can be considered in calculating the genotyping return on investment. Although still measured in years, a much shorter timeframe can be considered. Adopting similar reasoning to Calus *et al*. (2015) but modelling Australian dairy farms, Newton *et al*. (2018) showed that the net benefit of genotyping to guide heifer-replacement decisions on an 'average' farm with surplus heifer-replacement candidates is likely to be positive. They found that when the selection decisions were based on parent average-derived EBVs, the net benefit of genotyping was AU\$204 in a 100-cow herd in a scenario where all female progeny are tested. This increased to AU\$1124 when no EBV was available. Ultimately, the financial returns from genotyping to support replacement decisions are greatly influenced by individual farm parameters such as replacement rate, reproductive performance and current selection practices. However, being able to show that investments in herd improvement tools can be recouped within a short timeframe may support uptake of commercial genomic testing of heifers (Newton *et al*. 2018).

Other value propositions

Aside from performance and profit, there are other quantitative measures that can help demonstrate the value of herd improvement. Illustrations of the link between genetic improvement and environmental efficiency or risk are part of developing attractive value propositions for industry and farmers.

Measuring environmental value

Climate change and an increasingly conscious consumer interested in the environmental credentials of food production mean that there is a growing need to demonstrate the link between genetic improvement and environmental value. The Australian red meat industry has already announced a plan to be carbon neutral by 2030 (Mayberry *et al*. 2019), while in August 2020, peak farm body National Farmers Federation came out in support of a national carbon-neutrality strategy for 2050 (Murphy 2020). Without a price on carbon emissions in Australia, one approach for showing the value of herd improvement from an environmental perspective is to illustrate the direct link between genetic merit and carbon emissions.

Modelling undertaken by Pryce and Bell (2017) showed that over a 10-year period, cows selected using the BPI are expected to have 33% less carbon dioxide-equivalent emissions/cow.year than are those selected using the predecessor of the BPI. Over the past decade, there has been a reduction of 1% per year in total emissions from the Australian dairy industry (Pryce and Bell 2017), as the national dairy herd has decreased in size while production per cow has increased. This means that both genetic improvement in individual traits as well as improved selection indices are helping produce more environmentally friendly cows. Since 2015, breeding companies and Australian farmers have had the opportunity to breed for more efficient cows directly through the Feed Saved EBV (Pryce *et al*. 2014). Cows that have higher Feed Saved EBVs are more efficient and have lower total greenhouse gas emissions (Pryce and Bell 2017). Improvements in Feed Saved EBV are expressed to farmers as savings in feed not greenhouse gas emissions. One opportunity that would allow for divergent views on the value of genetic improvement to reduce carbon emissions would be to develop an additional 'green' index that ranks bulls on the basis of the expected carbon footprint of their daughters instead of expected profit. It is probably only a matter of time before a monetary value is placed on carbon dioxide emissions. Until then, illustrations of the link between genetic gain and reduced carbon dioxide emissions present a viable solution for illustrating the environmental value of genetic improvement.

Valuing risk

Assessing risk, that is, the uncertainty surrounding the consequences of an action (Anderson 1988), is an important part of any business. Two examples relevant to herd improvement are: (1) herd testing, which is perceived to reduce risk to farm businesses; and (2) genomic testing, which is perceived to increase risk to the farm business. We followed experiences of seven farms in introducing herd testing over a 15-month period. Among these farms, incorporating herd testing into their businesses was valued as a risk-reduction tool, with frequent expressions of more confidence in decision making (Newton *et al*. 2020). Additionally, several of these seven farms noted that cows sold with herd test records received higher prices. One farm explicitly stated herd testing was part of their risk-management

plan and was also a criterion of their bank for a loan (Newton *et al*. 2020). In direct contrast, herds that took up genotyping and that were questioned expressed concerns about the risk of adopting genomic testing in terms of how well it predicted future animal performance. The following approaches have been applied in practical scenarios to validate of the use of genomic EBVs (EBVgs). First, the realised reliabilities between pre-calving EBVgs and the corresponding first lactation production records were estimated as the squared correlation between EBVgs and EBVs calculated including first lactation production records. These ranged from 0.66 to 0.77, comparing well to the published mean production trait EBVg reliabilities of 0.74 of DataGene (Pryce *et al*. 2018*b*). Second, when heifers were classified into quartiles on the basis of their genomic BPI across herds, the group of heifers that ranked in the bottom 25% for genomic BPI (across herds) included no heifers that ranked in the top quartile for either actual protein or fat yield. A similar trend was seen within herds. On average, less than 2% of heifers that ranked in the bottom quartile for genomic BPI appeared in the top quartile for the actual protein yield. However, one herd had 15% of bottom quartile genomic BPI heifers that were in the top 25% for protein yield. This herd also had the poorest relationship between trait deviation and EBV (Pryce *et al*. 2018*b*). These results showed that EBVgs are a reliable predictor of future herd performance, with a low risk of accidently selling a genetically elite heifer. They also provide independent evidence of the accuracy of EBVgs in Australia, indicating that EBVgs can be confidently used to guide heifer selection decisions (Pryce *et al*. 2018*b*).

In a herd improvement context, risk is not often measured or valued explicitly, although EBV accuracy (or reliability) is often used as a substitute. Newton *et al*. (2017*a*) proposed that probability distribution theory could be used to quantify the relative risk of different breeding programs, including several considering the incorporation of genomic EBVs. In placing a value on risk, Klieve *et al*. (1993) and Rogers (1990) explored strategies for ranking sires on the basis of both genetic merit and risk. They found that the overall impact on ranking was small, unless a very high aversion to low accuracy sires existed. A risk-reduction strategy has been adopted to a degree in Australia; to be published in the Good Bulls Guide, sires have to meet several criteria, including a minimum reliability. As genomic reference populations continue to grow, and novel analyses are developed, it is also feasible that new approaches for valuing genetic risk will be developed. For example, computational techniques developed to calculate inbreeding or that identify lethal recessive allele combinations (Maltecca *et al*. 2020) could extend valuation of risk beyond EBV accuracy.

Capturing value generated by additionality

Additionality, where further value is garnered from a piece of information by its use many times, theoretically helps build more attractive value propositions by lowering cost per use; however, capturing this on-farm value is challenging. For example, it is widely accepted that additional genetic gain through more accurate selection of herd replacements

represents only part of the on-farm return expected from female genotyping (Pryce and Hayes 2012; Boichard *et al*. 2013). However, selection of herd replacements has been the most frequently modelled because of its ease of measurement. In practice, the availability of EBVg is likely to result in other changes on farm such as usage of sexed dairy semen, or beef semen or both sexed dairy semen and beef semen as modelled by McCullock *et al*. (2013), Newton *et al*. (2018) and Bérodier *et al*. (2019). The availability of accurate EBVs on young animals also presents opportunities on farm, including changes to calf rearing strategies, changes to cow culling strategies, new markets due to validated pedigrees or EBVg or both, optimised mating programs or managing inbreeding. Farmers may also have very specific business reasons for genotyping, applicable to only a percentage of farmers, such as a transition to A2A2 milk or polled animals. Such changes are likely to be quite farm-specific and hard to quantify more broadly.

The difficulties in quantifying additionality was particularly apparent in valuing the adoption of herd testing on farm. While specific examples of data usage were quantified (Newton 2017), farmer interviews identified that data were used multiple times and in different ways across farms (Newton *et al*. 2020). For example, a 6% loss in milk income due to milk quality penalties was able to be corrected after herd test information enabled high somatic cell count cows to be identified. Similarly, the flow-on effects of a decision to dry-off cows early where quantified through additional milk production and savings in concentrate fed and milking labour costs (Newton 2017). In both examples, a single usage of data recouped the entire cost of herd testing in a season. However, capturing a monetary value of all data uses was virtually impossible. Here, qualitative analytical approaches offered additional opportunities for illustrating the value of herd improvement. Qualitative analysis showed strong themes around confident, informed decision making (i.e. risk reduction). After having herd testing paid for by research projects, the managers of all seven farms involved in our study decided to continue or resume herd testing after the project finished and they had to pay for tests themselves. This willingness to pay for herd testing is a clear demonstration of herd testing being perceived as valuable (Newton *et al*. 2020). Arguably, the best strategy for developing value propositions that capture data additionality is to combine qualitative and quantitative measures of value.

Demonstrating value to drive practice change

No one illustration of value for herd improvement is going to fully capture data additionality or resonate with all target audiences, or even individuals within a target audience; however, it is possible to develop value propositions that increase farmer usage of herd improvement tools. Having a multi-faceted value proposition, including qualitative and quantitative measures of value developed in conjunction with farmers and dairy industry stakeholders, is an approach that gets involvement and action, as we have demonstrated through examples of applying it to herd improvement challenges. Following previous recommendations around demonstrating on-farm value propositions (Nettle *et al*.

2010) and directly involving farms (Crawford *et al.* 2007), communication and early extension activities were incorporated within a research project that used many of the case studies presented here. This structure facilitated the involvement of representatives from right across the herd improvement space throughout the project. While this created some challenges, especially in terms of timing, this model facilitated iterative feedback cycles on the project methodology and messaging and realised new opportunities. Having farms involved in research projects also supported the development and piloting of extension resources and created a platform where farmers could learn from one another, which is their preferred method of learning (Blair *et al.* 2013). The farms involved also increased their knowledge base and became advocates for genetics and herd improvement. This 'farmer voice' has been a very effective way of disseminating project material, in a relatable way that can effect change in farmers. For example, at the end of a herd improvement field day that included many of the examples presented in the current paper, 86% of the respondents to a survey ($n = 72$) said that the day had 'changed their thinking' about utilising genetic information on farm.

Conclusions

There is no single unifying number that demonstrates the value of herd improvement. Instead, demonstrating the value of herd improvement to the dairy industry, or any livestock sector, requires a multi-faceted approach. Valuation needs to extend beyond monetary worth to also consider risk, environmental value as well as qualitative assessments of value, being cognisant of the fact that data additionality means that full value is unlikely to be captured. The target audiences need to be considered in developing a value proposition as perceptions of value differ both among and within stakeholder groups. Value propositions developed in consultation with dairy stakeholders that feature on-farm case studies facilitate the development of value propositions that resonate with farmers and can lead to increased uptake and confidence in herd improvement tools and information. It is recommended that current monitoring of herd improvement progress be supplemented with regular assessments of the value of the tools that underpin herd improvement. These valuations should be multi-faceted and consider non-monetary and non-quantifiable measures of value. Such value demonstration, particularly at the farm level, is important for fostering uptake of new or improved tools as they are released to industry.

Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgements

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